THE ROLE OF THE COMMUNITY COLLEGE IN TEXAS: THE IMPACT OF ACADEMIC INTENSITY, TRANSFER, AND WORKING ON STUDENT SUCCESS

By

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The conclusions of this research do not necessarily reflect the opinions or official position of the Texas Education Agency, the Texas Higher Education Coordinating Board, or the State of Texas.

To the memory of Grandma Tack,
who inspired me.

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CHAPTER I

INTRODUCTION

Community colleges represent a vital segment of American higher education, enrolling 42% of all undergraduate students nationally. Yet, while nearly 80% of first-time students who enroll in a community college intend to obtain a bachelor's degree, only 23% do so within six years (U.S. Dept. of Education, 2005). Indeed, in Texas, over 50% of first-time undergraduates are enrolled in community colleges, yet only 14% of students who begin in the community college earn a bachelor's degree within six years (US Department of Education, 2010; Texas Higher Education Coordinating Board, 2010).[1] In recent years, a growing reliance on community colleges has been exacerbated by capacity constraints at four-year institutions (Evelyn, 2002) as well as increasing admissions criteria and soaring tuition in the four-year sector (Mills, 2006). As a result, many more students are enrolling in the community college directly from high school (U.S. Dept. of Education, 2005).

With these soaring numbers, a great debate exists today, more than ever before, over the role of the community college as a democratizing agent that expands student enrollment or a diversion tool that prevents students from attaining an undergraduate degree (Alfonso, 2006; Cohen & Brawer, 2008, Dougherty, 1987; Gonzalez & Hilmer, 2006; Leigh & Gill, 2003; Long & Kurlaender, 2009; Melguizo & Dowd, 2009; Rouse, 1995). From their inception, many believe

[1] It must be noted, however, that national figures are calculated only for those who indicate a clear intention to complete a bachelor's degree whereas Texas statistics are reported for those all students enrolling full time, making direct comparisons misleading. It remains clear, however, that degree attainment remains low for students beginning at the community college level in Texas.

community colleges have expanded higher education to provide postsecondary training for many—to democratize education—and prepare a pathway to undergraduate degree attainment for disadvantaged students (Cohen & Brawer, 2008). Critics of the community college system claim that such expansion in the two-year sector has further stratified American society by diverting disadvantaged students away from a four-year institution where they would have likely earned an undergraduate degree (Brint & Karabel, 1989; Labaree, 1997).

With enrollment in the community college sector swelling and a scholarly debate over the role of the community college raging, I seek to explain the community college enrollment, persistence, and success story in Texas—a state second only to California in the number of community college students it enrolls (U.S. Dept. of Education, 2005). In addition, I focus solely on those students who enroll in the community college immediately after graduating from high school. These students, perhaps once considered non-traditional, are quickly becoming more traditional in the sense that many more students are electing to enroll immediately in the community college sector as the four-year sector becomes increasingly crowded and cost-preventative (Evelyn, 2002; Mills, 2006). At the superordinate level, I address the current role of the community college by way of three questions: (1) How can we increase transfer from the community college into the four-year sector? (2) What happens to successful transfer students as compared to their four-year peers? and (3) What is the overall enrollment story for community college students and how does increased wages earned while enrolled affect degree outcomes?

Objectives

To better understand the role of the community college, I examine three specific pathways. First, I investigate the transfer process between two- and four-year institutions using a matching technique. Second, I examine the degree attainment patterns for those students who successfully transfer to a four-year school in comparison to their peers who initially began in the four-year sector using a two-stage sample selection model. Third, I explore the factors associated with overall undergraduate degree attainment for those students beginning at the community college with a particular focus on working while simultaneously enrolled using event history analysis. Indeed, with regard to each pathway, I explore the relationship of wages earned prior to enrollment as well as income earned while concurrently enrolled. What follows is a brief review of the national context of community college, as well as a particular focus on Texas.

National Context

Nationally, nearly 80% of first-time students who enroll in a community college intend to obtain a bachelor's degree; however, only 23% are successful in doing so within six years (U.S. Department of Education, 2005). In terms of student success, disadvantaged students have the lowest overall completion rates (Cabrera, Burkum, & La Nasa, 2005) and the lowest transfer rates (Melguizo, 2006; Dougherty & Kienzl, 2006). Why are so few students who begin at a community college unable to complete a bachelor's degree? Potential answers to this sweeping question may lie in such areas as poor academic preparation before graduating from high school, a lack of articulation agreements between community colleges and four-year institutions, and/or a lack of support in either the two- or four-year sectors (Kane, 1999; Rouse, 1998; Leigh & Gill, 2003; Wassmer et al., 2004).

In a descriptive study using data from the National Center for Education Statistics, Bradburn and Hurst (2001) find that transfer rates are significantly higher for those students who (1) initially enroll in an academic degree program, (2) intend to complete an undergraduate degree, and (3) remain continuously enrolled during the first two years of their postsecondary education. Multivariate analyses of community college transfer rates and eventual degree attainment point to differences between pre-college academic preparation (Melquizo & Dowd, 2009), sex (Surette, 2001), race (Lee & Frank, 1990), economic status (Melguizo & Dowd, 2009), and institutional factors such as tuition and fees (Shulock & Moore, 2005).

Research by Adelman (1999, 2004, 2006), points to another potential way in which degree completion may suffer: a lack of academic intensity in the first year of enrollment. One definition of academic intensity Adelman tests is that of the number of credits earned during the first year of study, finding that students who earn fewer than twenty credits in the first year of coursework are at significant disadvantage for eventual degree attainment (Adelman, 2006). In a recent study, Doyle (2009) utilizes a matching technique to explore the relationship between credits taken during a student's first semester at the community college and their eventual transfer to the four-year sector, finding that taking twelve or more credits increases the probability for transfer by at least 11%. I employ a similar technique in order to understand the effect of full time enrollment on successful transfer from a community college to a four-year institution in Texas.

For community college students, and particularly for disadvantaged students who are disproportionally represented in the two-year sector (Bailey, Jenkins, & Leinbach, 2005), transfer to a four-year institution is critical in undergraduate degree attainment. Even after successful transfer, however, those who begin in the community college may face challenges in achieving an undergraduate degree. To explore this issue, Melguizo and Dowd (2009) compare degree attainment for those students who began at a community college and successfully transferred to four-year institution to those students who began in the four-year sector and have successfully completed two academic years of study. After controlling for such factors as race, socioeconomic status, and academic ability, as well as accounting for selection bias, the authors conclude that the diversion factor (community colleges diverting students away from attain a four-year degree) decreases and, after controlling for state-level policies, the diversion factor vanishes. In this study, I appeal to the work of Melguizo and Dowd (2009) to better understand the impact of beginning at a community college as compared to those students beginning at a four-year institution.

Additionally, Bound et al. (2007) find that increased hours of employment among college students arises due to a need to meet soaring tuition costs and has a pronounced affect on the amount of time for such students to complete an undergraduate degree. To better understand the overall story of degree completion for community college students, I appeal to many of the aforementioned factors and then focus on the impact of wages earned while concurrently enrolled to better understand the completion story for working students.

A Focus on Texas

In Texas, over 50% of undergraduates are enrolled in community colleges. Furthermore, Texas enrolls nearly 9% of community college students, nationally—a share exceeded only by California. (United States Department of Education, 2010). Despite this sizeable enrollment, only 14% of those students who begin in the community college earn a bachelor's degree within six years (Texas Higher Education Coordinating Board, 2010). It must be noted, however, that national figures are calculated only for those who indicate a clear intention to complete a bachelor's degree whereas Texas statistics are reported for those enrolling in 12 or more credits, making direct comparisons misleading. It remains clear, however, that degree attainment remains low for those students beginning at the community college in Texas.

Within the last fifteen years, Texas has undergone significant policy shifts aimed at increasing student access and success that, in many cases, have had a national impact. Following the *Hopwood v. Texas* federal case that allowed race as a factor in college admissions, in 1998 Texas implemented the Top Ten Percent Plan granting admission to Texas public institutions to all students graduating in the top ten percent of their high school class. Shortly thereafter, in 2001, Texas became the first state in the nation to pass an in-state resident tuition bill providing undocumented students the opportunity to attend college at the same tuition rate as in-state students (Olivas, 2004; Flores, 2010). At the institutional level, The University of Texas System and several campuses of the Texas A&M system became pioneers in the public college sector by creating "no-loan" programs whereby eligible students would receive additional financial assistance from the institution in order to eliminate student loans (working papers: Flores, McLendon, Park & Mavrogordato, 2010; McLendon, Flores & Park, 2010).

With particular regard to the community college sector, several community colleges within Texas have partnered with *Achieving the Dream,* a national initiative to improve degree attainment for community college students. In addition, four Texas community colleges (Coastal Bend Community College, El Paso Community College, Houston Community College, and South Texas College) have been selected by the Bill and Melinda Gates Foundation to receive grants aimed at increasing the effectiveness of developmental education (see www.tacc.org/dream.htm). At the state policy level, the Texas Association of Community Colleges (TACC) proposed a new policy initiative, known as the New Compact, to the 80th Texas Legislature. Contained in this policy initiative are proposals to increase accountability on behalf of the state's community college campuses in terms of student participation and success as well as an initiative to keep tuition low and provide more need-based financial aid. TACC continues to advocate for the New Compact with the 81st state legislature.

The higher education landscape in Texas is massive and, in particular, so is the community college sector. With fifty community college districts in the state, TACC oversees over 735,000 community college students. This represents over 50% of all postsecondary students in Texas and well over 55% of all students enrolled in public higher education (THECB, 2010). Previous studies have examined community colleges in national contexts (e.g. Melguizo & Dowd, 2009) as well as other states with sizeable community college enrollments (e.g. Long & Kurlaender, 2009) and a few have begun to examine the community college sector in Texas (e.g. e.g. Bobby et al., 2003; McFarlin, Jargowsky & Holovchenko, 2005; O'Brien & Nelson, 2004); however, to the best of my knowledge, no other study has provided an extensive investigation of the role of the community college in Texas. I turn now to presenting the specific research questions.

Research Questions

The purpose of this work is to better understand the role of the community college in undergraduate degree attainment in Texas. In order to probe this relationship, I divide the project into three parts, each requiring a different, though related, approach. I ask the following three sets of research questions—with regard to each of the questions, I explore the outcomes by race and economic status.

(1) What is the impact of full time enrollment during the first semester on eventual transfer to a four-year college or university for students graduating from high school and immediately enrolling in the community college?

(2) What is the effect of initial enrollment in a community college on eventual degree attainment for students graduating from high school, immediately enrolling in the community college and successfully transferring to a four-

year college or university as compared to students who began in the four-year sector?

(3) What factors, and specifically the role of wages earned while concurrently enrolled, contribute to eventual undergraduate degree attainment for those students graduating from high school and immediately enrolling in the community college?

Statistical Approach

Given the three-pronged nature of this project, separate—but related—statistical approaches are offered, below. In all cases, I extensively use a relatively underutilized, though rich, confidential, dataset: the Texas Schools Microdata Panel (TSMP). The TSMP is a restricted use administrative dataset that includes information on secondary school records and postsecondary education outcomes from 1992 through 2010. In addition, I access individual wage information from the Texas Workforce Commission by utilizing a dataset containing income data on each Texas resident over the same timeframe. The combination of these datasets provides a wealth of information only recently used for education research.

I have served as a research assistant for Dr. Stella Flores since early 2009, who has two approved projects funded by the Gates Foundation utilizing this dataset. The Texas Joint Advisory Board, the organization that grants research access to this restricted dataset, approved a formal proposal for my own dissertation work in December 2010. Aside from the TSMP, I also access outside sources such as the Texas Comptroller, the Common Core of Data, and the

Integrated Postsecondary Education Data System. Institutional Review Board approval was granted for this project in January 2011. What follows is a discussion of the intended approach for each of the three designs.

RQ 1: The Impact of Full Time Enrollment on Transfer

I seek to better understand the role of full time enrollment—and, specifically, taking 12 or more credits—during the first semester of community college enrollment on eventual transfer to a four-year institution. I utilize a matching technique to reduce inherent selection bias and move towards the identification of an unbiased estimate of the effect of full time enrollment on transfer to a four-year school (Rubin, 1974, 1976; Rubin & Neal, 2000; Reynolds & DesJardins, 2009). Essentially, I seek to match students on a number of key covariates and then test the impact of full time enrollment on only those matched students in order to obtain a "true" effect of credit hours. Key to any study utilizing matching is a rich set of covariates on which to match students in order to establish two balanced groups—those who took a certain threshold of credit hours and those who did not.

Using the TSMP data, I create cohorts of community college students who enroll directly from high school. By linking data from both the secondary and postsecondary data records, I match on such characteristics race and sex, pre-college academic preparation, economic capacity, and high school context. By combining data from sources such as the Bureau of Economic Analysis and the Texas Comptroller, I match on characteristics such as county unemployment rate.

RQ 2: The Effect of Beginning at a Community College on Degree Attainment

For students who have successfully transferred to a four-year institution, I seek to better understand the effect of beginning at a community college as compared to their peers who began in the four-year sector. In addition to the array of covariates outlined in the previous research question, I also include such postsecondary information as the number and academic designation of credits taken at the four-year institution. Also, I incorporate institutional-level covariates from the Integrated Postsecondary Education Data System (IPEDS). This regression analysis uses students in their third year of study at a four-year institution as a comparison group for transfer students from the community college sector.

In this model, I am primarily interested in the effect of beginning at a community college on degree attainment. A potential source of bias in any estimation of this effect is that of self-selection. Most simply, self-selection bias arises in the event that there are certain unobservable factors (for instance, motivation) that contribute to a student self-selecting into a community college as opposed to a four-year institution. To account for this bias and move towards a unbiased relationship, Heckman (1979) and Lee (1983) support the use of a two-stage selection correction model. Using this approach involves the identification of a factor that predicts enrollment in a community college, but does not predict eventual degree attainment. This factor "identifies" the first-stage regression and allows for an unbiased estimate in the second stage. Specifically, I estimate the predicted probability of being a community college transfer student by using a combination of proximity to postsecondary institutions, higher education cost data, and lagged local unemployment rates as a method to identify the selection equation. This selection method is supported by Melguizo and Dowd (2009) as well as Long and Kurlaender (2009). With the wealth of information available from the TSMP dataset, as well as an appropriate instrument, I move towards an unbiased estimate of the relationship between community college transfer and degree attainment. Doing so, however, is largely dependent on the strength of the instruments; as such, I employ standard tests for validity of the instruments and, as an additional test of the relationship, I also implement a matching strategy similar to that outlined in research question one, above.

RQ 3: Overall Factors Contributing to Degree Attainment for Community College Students, Focus on Wages.

Overall, I seek to better understand how different factors—and specifically wages earned while concurrently enrolled—affect not only a dichotomous outcome of having completed an undergraduate degree, but also a temporal factor of *when* the degree is completed. As such, I turn to Event History Analysis (EHA). Simply put, EHA is able to predict the risk of an event (degree completion) occurring at a particular point in time by employing a hazard function. In addition, in a multivariate model, the hazard function coefficients for the covariate provide information regarding how the explanatory variables influence the hazard rate. Due to the nature of the data, I use a discrete time model where temporal change is measured in terms of academic semesters. In addition, I expand the model to forecast not only those factors associated with degree attainment, but also those connected to stopout behavior and re-enrollment.

Variables of interest include wages earned as well as such characteristics as race, sex, economic status, academic intensity in high school (completing Advanced Placement and/or International Baccalaureate courses as well as completing a trigonometry course), performance on the statewide mathematics exam, high school characteristics (pupil-teacher ratio, overall enrollment, percent minority, per-pupil expenditures, and urbanicity), and community context data. With regard to postsecondary education, event history analysis has become increasingly more popular in the study of enrollment behavior (e.g. DesJardins et al., 1999, 2002; DesJardins, 2003). The results of this analysis shed light on the time-varying covariates that contribute to degree attainment for students beginning at the community college.

Contributions to Theory and Practice

Central to this project is providing a comprehensive and contemporary view of the role of the community college in undergraduate degree attainment. This project is particularly timely given the recent community college summit at the White House in early October 2010 where President Obama reinforced public faith in the community college as an important pathway to an undergraduate degree. At the same time, the Gates Foundation announced its commitment to funding a $35-

million project aimed at increasing the graduation rates of community college students (The White House, 2010). With such an increased focus on community colleges and far too many students failing to attain an undergraduate degree, it is paramount that we better understand the role of the community college so as to better inform research, policy, and practice. In order to complete a detailed, yet representative analysis, I have selected Texas for the setting of this study—a state with one of the largest community college systems in the country as well as a growing and diverse student population.

The student unit record dataset in Texas provides the opportunity to expand upon the existing body of knowledge and tap into a vast wealth of previously unexplored factors. Furthermore, the TSMP data in Texas provides the opportunity to conduct analyses across several cohorts over recent years. Working papers using the TSMP data have begun to lay a strong foundation upon which future research on the Texas community college may be built (e.g. Bobby et al., 2003; McFarlin, Jargowsky & Holovchenko, 2005; O'Brien & Nelson, 2004). Given the ever-changing landscape of the community college sector, this level of information is essential to understanding the complex role of the community college. With rising enrollment in the community college sector and recent policy changes geared at increasing student success, as well as significant social, political, and economic shifts within its borders, Texas stands to become a pioneer in practices and policies related to the community college.

By better understanding the role of the different factors that affect transfer between community colleges and four-year institutions, and specifically the role of full time enrollment in the first semester at a community college, Texas will be able to make a more informed decision on offering incentives to community college students to encourage transfer. Additionally, by better understanding both the transfer process and the pathway to eventual degree attainment for community college students, Texas will be able to enhance support mechanisms for successful community college transfers upon arrival at a four-year school. Finally, by better understanding the overall story of degree attainment for community college students and the influences of working while enrolled, Texas will be able to make more informed decisions regarding a growing segment of its higher education landscape to which it has a firm commitment.

Unlike other analyses, this project has the added benefit of using a vast dataset and incorporating such information as pre-college factors, employment data while students are enrolled, and coursework completed in both the two- and four-year sectors. Given the composition of the state and its vast higher education landscape, it is likely that lessons that lessons learned in Texas will be applicable to other systems, as well. Finally, this project seeks to better inform the very entity which it studies: students beginning at the community college, by shedding light on the factors associated with eventual degree attainment to allow college-going students to make a more-informed enrollment decision.

Limitations

This study is subject to several limitations. First, I include only those students who graduated from a public high school in Texas due to data availability. While this decision rule will likely exclude a small handful of students enrolled in the Texas higher education system, I argue that the students most likely to enroll in the community college sector (the target population of interest) are also those students most likely to have graduated from a public, in-state high school. Furthermore, this approach allows for the inclusion of a rich set of covariates pertaining to high school context. Second, this study is limited to only those students who enroll in institutions of postsecondary education in Texas. While not nationally representative, I argue that results gained from this study will contain elements of external validity due to the vast landscape of higher education in Texas and the wide variety of students enrolled in the postsecondary system. Finally, the structure and availability of the data permit the analysis of only four cohorts of students. I argue, however, that this will present a robust estimation of the role of the community college giving at least four years of data over which to compare results.

General Overview

This dissertation is organized as three essays detailing the degree completion process for community college students. Chapter II investigates the role of full time enrollment in the first semester on transfer rates. Chapter III probes the impact of beginning at a community college as compared to peer students who began at a four-year institution. Chapter IV explores the overall factors influencing degree completion, with a focus on working while simultaneously enrolled. Finally, Chapter V contains a discussion section, a section on policy implications, theoretical contributions, and directions for future research. In addition, Chapter V contains an overarching discussion section.

CHAPTER II

THE IMPACT OF FULL TIME ENROLLMENT IN THE FIRST SEMESTER: AN ANALYSIS OF COMMUNITY COLLEGE TRANSFER RATES USING MATCHING ESTIMATORS

Introduction

Community colleges represent a vital segment of American higher education, enrolling 42% of all undergraduate students nationally. Yet, while nearly 80% of first-time students who enroll in a community college intend to obtain a bachelor's degree, only 23% do so within six years (U.S. Dept. of Education, 2005). At the state-level, we see even more compelling in figures. In Texas, a state that enrolls nearly 9% of community college students nationally (a share exceeded only by California), over 50% of first-time undergraduates are enrolled in community college, yet only 14% of students who begin in the community college earn a bachelor's degree within six years (US Department of Education, 2010; Texas Higher Education Coordinating Board, 2010).[2]

How could we improve student success? A key step in earning a bachelor's degree that has begun to receive a resurgence of attention is the transfer process between community colleges and four-year schools. While some state-level policies have focused efforts on articulation agreements between community colleges and four-year institutions, others have explored another way to improve successful

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transfer: encouraging, incentivizing, and/or requiring full-time enrollment at the community college for those students intending to transfer. In 2001, the Connecticut Community Colleges system began using a state longitudinal financial aid database to track student aid and overall success. With this system, students in Connecticut are now able to make more informed enrollment decisions, including enrollment status, by reviewing different enrollment and financial aid scenarios with community college personnel (Connecticut Community College System, Financial Aid Services, 2011). Evidence from Connecticut demonstrates the soaring cost of enrolling part time, both in terms of financial burden on the student and overall impact on eventual degree attainment (College Board Advocacy & Policy Center, 2010). Building on this model, California has begun an initiative to inform students of the financial benefit of enrolling full time whereby financial aid officers first ask students the number of credits they intend to take and then work out different simulations demonstrating the amount of money underutilized by enrolling part time (Moltz, 2011).

Alongside these initiatives is that of the City University of New York's (CUNY) New Community College initiative, that, when originally proposed in 2008, presented a new concept to the community college sector: *requiring* students to enroll full time with the intent to improve and expedite degree attainment (The City University of New York, 2008). Though some were initially critical of this initiative (see Moltz, 2009), in a September 20, 2011, letter to Education Commissioner John B. King, Jr., New York Governor Andrew Cuomo approved the creation of the New Community College (The City University of New York, 2011). Through the creation of this community college, CUNY stands at the forefront of policy initiatives geared directly at improving student success by focusing on full time enrollment.

The success of these credit load policies, however, rests in the notion that full time enrollment will substantially increase transfer rates. In order to better understand this relationship I build on an existing—though scant—literature and ask, "For those students beginning at a community college, what is the effect of full time initial enrollment on successful transfer to a four-year institution?" What follows is a review of the literature surrounding community college success, with a particular focus on the transfer process and the role of a full-time credit load in the first semester.

Literature Review

This literature review is organized into three sections. First, I discuss the theoretical framework used to guide and provide justification for the notion that full-time status will increase student success. Second, I present correlational findings that appear to support this hypothesis. Finally, I review the existing empirical studies examining community college student success with a focus on credit-taking behavior and its impact on transfer.

Theoretical Framework

The notion that full-time enrollment will positively affect student success is tightly linked to earlier work on the connection between increased student engagement and success. Student engagement represents the time as well as the energy put forth by students in educational activities as well as the institutional effort to use effective educational strategies (Kuh, 2001). Early studies have shown that students who are less engaged are less likely to experience academic success (e.g. Hughes & Pace, 2003). For many years, however, research on student engagement and its relationship to student success has been focused at single institutions and has failed to incorporate information on student background characteristics (Pascarella & Terenzini, 2005). As such, these early studies were limited in their generalizability to other populations.

Recently, though, studies have begun to use large-scale data sets from multiple institutions (e.g. Kuh et al., 2008). For example, correlational findings from the National Survey of Student Engagement (Kuh et al., 2005) suggests that students who are more engaged—through feeling academically challenged, participating in an active and collaborative learning environment, participating in increased student-faculty interaction, enjoying enriching educational experiences and supportive campus environments—are more likely to succeed in college.. Furthermore, research indicates that those students who spend more time on campus and are enrolled in higher course loads are more likely to be highly engaged, and, as a result, more likely to experience academic success (Kuh, 2005). While acknowledging that student success can take many forms (Braxton, 2006; Kuh et al., 2007), I look specifically at the role of increased course loads by way of full time enrollment and its impact on community college transfer. I uniquely contribute to the literature by examining this impact in a multi-institutional fashion using a myriad of pre-college individual characteristics.

Specific to community colleges, recent literature reveals that students enrolled in more credits are typically present on campus in much higher frequencies and more deeply engaged both inside and outside of the classroom (Center for Community College Student Engagement, 2009). This overall student engagement, in turn, has been linked tightly by several studies to overall student success, as well as to community college students, in particular (e.g. Schuetz, 2008). This is particularly telling given that community college students tend (on average) not to live on campus and thus the opportunity for engagement is even more so linked to time spent on campus through credit hours (CCCSE, 2009). I argue, therefore, that full time enrollment will increase community college student engagement and thereby positively impact successful transfer to a four-year institution for those students intending to earn a baccalaureate degree. I turn now to correlational findings that appear to support this notion.

Correlational Findings

In a descriptive study using data from the National Center for Education Statistics (NCES), Bradburn and Hurst (2001) find that transfer rates are significantly higher for students who (1) initially enroll in an academic degree program, (2) intend to complete an undergraduate degree, and (3) remain continuously enrolled during the first two years of their postsecondary education. Research by Adelman (1999, 2004, 2006) also points to the influence of academic intensity in the first year of enrollment at a community college. One definition of academic intensity Adelman tests is the number of credits earned during the first year of study, finding that students who earn fewer than twenty credits in the first year of coursework are at a significant disadvantage for eventual degree attainment (Adelman, 2006). Taken collectively, the existing literature, both theoretical and correlational, suggests that students who enroll full time will be more engaged and more likely to succeed.

Empirical Studies

Recent empirical studies of college student success investigate differential outcomes along such lines as (1) sex (Surette, 2001) and race (Lee & Frank, 1990), (2) pre-college academic preparation (Bound, Lovenheim, & Turner, 2009), (3) economic status (Melguizo & Dowd, 2009), and (4) high school context (Fletcher & Tienda, 2010). As such, I include indicators for these four broad areas as controls; a more complete description of the measures used for the indicators as well as a specific justification from the literature for each is included in the research design section.

To date, however, the vast majority of empirical studies on college student success have often focused on either the four-year sector or solely on overall degree attainment for community college students. Only recently has the field begun to rigorously explore transfer and degree attainment after successfully transferring as separate processes, gaining valuable information from each (Doyle, 2008; Melguizo & Dowd, 2009). In a recent study, Doyle (2008) explored the relationship between credits taken during a student's first semester at the community college and their eventual transfer to the four-year sector, finding that enrolling full time (taking twelve or more credits) increases the probability for transfer by at least 11%.

Still, though, recent studies on community college success have been limited to extent to which they are able to construct sizeable samples and include a rich set of student-level covariates. Melguizo and Dowd (2009) make use of NCES' *National Educational Longitudinal Survey Class of 1992* (NELS: 88/2000). While taken from a nationally representative dataset, their subset provides the researchers with only 1,034 viable observations (247 community college transfer students, and 787 four-year students). Doyle's (2008) study is unable to account for a number of important pre-college factors known to influence academic success, including academic preparation from high school as well as high school and community context. In addition, while recent work from Ohio by Long and Kurleander (2009) incorporates pre-college factors, their analysis did not include a valuable covariate available in Texas: employment data.

As Cohen and Brawer (2008) report, community college students tend to have higher numbers of working hours and also tend to be less likely to succeed as a result of increased demands in the workplace. This study has the unique benefit of including a control for wages earned during the first fall semester at the community college as an additional covariate. Working is a large component of the lives of many community college students and, as such, I include the role of wages earned in the fall semester in order as an additional control to tell a more complete story of the community college transfer experience.

The correlational findings from Adelman (1994, 2004, 2006) and previous findings using matching techniques from Doyle (2008) suggest a link between enrollment status in the first semester and eventual transfer. I extend this body of knowledge by applying a quasi-experimental technique in a new setting and using a richer dataset, asking: "For those students beginning at a community college, what is the effect of full time initial enrollment on successful transfer to a four-year institution?" What follows is a presentation of the research design, followed by a results section and a sensitivity analysis.

Research Design

Counterfactual Framework

A naïve estimator of mean comparisons between those students who do enroll full time compared to those students who do not demonstrates that those students who enroll full time are more likely to transfer than those who enroll in only a few courses (Adelman, 1999, 2004, 2006). While this could be the result of a causal pathway, there may be other factors influencing student enrollment as well as success. For instance, a student who enrolls full time may be better prepared academically, have a stronger financial situation, and have access to other forms of capital that those taking fewer courses simply do not possess. In addition, these same factors that may influence a student to enroll full time are also likely to influence whether the student is more apt to transfer. In essence, a simple comparison between those students who did and did not enroll full time would overestimate the impact of full-time enrollment on successful transfer. Thus, it becomes difficult to capture a "true" impact of full time enrollment on transfer rates. From a policy standpoint, this presents a significant problem. If measures are to be taken to improve student success, unbiased estimates and pathways must first be understood.

In this paper, I establish a counterfactual: a group of students who are similar on all fronts excepting only for full time enrollment, which will become the basis for the following analyses (Rubin, 1974, 1976; Reynolds & DesJardins, 2009). First, imagine a simple treatment situation. The variable y_{i1} represents the transfer outcome for those students who enrolled full time (12 of more credits) and the variable y_{i0} represents those students who did not.[3] Thus, the impact of full-time enrollment for any student (Δ) is given by (Smith & Todd, 2001):

$$\Delta = y_1 - y_0$$

The difficulty, however, is that I cannot observe outcomes for any student who simultaneously does and does not enroll full time (Holland, 1986). Instead, I am able to observe outcomes for two groups of students: those who did enroll full time and those who did not. As such, let $z = 1$ represent those students who enrolled full time and $z = 0$ represent those who did not. As discussed, there may be other factors beyond credit hours that may explain the transfer outcomes for these students; I denote these factors as a vector of student characteristics, $\boldsymbol{x}$. In the social sciences literature, the mean impact of the average treatment on the treated (ATT) estimates the effect of the treatment for those receiving the treatment (in this case

[3] Full time enrollment is defined as 12 of more credit hours and was chosen, in part, due to the Federal Government's definition of full-time undergraduate status as 12 credits, thus enabling students to receive federal financial aid.

enrolling, full time) with respect to what the outcome would have been for the same individual students if they had not received the treatment (Smith & Todd, 2001), expressed as:

$$ATT = E(\Delta \mid x, z{=}1) = E(y_1 - y_0 \mid x, z{=}1) =$$

$$E(y_1 \mid x, z{=}1) - E(y_0 \mid x, z{=}1)$$

In this analysis, data is available for the mean outcomes among the treated [$E(y_1 \mid x , z{=}1)$], what is not known, however, is information about the counterfactual outcome [$E(y_0 \mid x, z{=}1)$]. In randomized studies, data on the counterfactual is provided in the control group, provided that the groups were randomized along the characteristics $\boldsymbol{x}$ (Heckman, 1979). Given this problem, economists have turned to such modeling approaches as instrumental variable as well as semi-parametric and non-parametric approaches including regression discontinuity designs (Lemieux & Milligan, 2006). For the purpose of this study, however, I turn to the non-parametric approach known as propensity score matching (Rubin, 1974, 1976). This sort of matching is able to overcome the problem of selection bias with the creation of a counterfactual group similar to the treatment group and has become increasingly more popular in the field of education research (Agodini & Dynarski, 2004; Doyle, 2008). What follows is a brief discussion of this method.

Matching Technique

Essentially, I seek to match students on a number of key covariates and then test the impact of full-time enrollment on only those matched students in order to obtain a “true” effect of credit hours. First, define the matching estimator: α. This estimator is identified by comparing the outcomes for the "treatment" group (those enrolling full time) with the "control" group (those not enrolling full time) conditioning on a common probability for selecting into the "treatment" group, p (Smith & Todd, 2001):

$$\text{Let } \alpha = E(y_1 - y_0 \mid z{=}1) =$$

$$E(y_1 \mid z{=}1) - E_{p|z=1}\, E_y\, (y \mid z{=}1, p) =$$

$$E(y_1 \mid z{=}1) - E_{p|z=1} E_y(y \mid z{=}0, p)$$

In addition, the probability p is defined as (Smith & Todd, 2001):

$$\Pr(z{=}1 \mid x) < 1 \text{ for all } x$$

Assuming this condition holds, I define the matching estimator for α as:

$$\alpha_M = \frac{1}{n_1} \sum_{i \in I_i \cap s_p} [\, y_{1i} - \widehat{\mathrm{E}}(y_{0i} \mid z = 1,\ p_i)]$$

Where $\widehat{\mathrm{E}}(y_{0i} \mid z = 1, p_i)$ represents the matched outcome and can also be written as $\sum_{j \in I_0} W(i,j)\, y_0$. In this case, I_1 is the treatment group (those who enrolled full time) and I_0 is the control group (those who did not). S_p is the region of common support between the two groups and n_1 is the number of individuals in in the set $I_1 \cap S_p$. The match, then, for each treatment individual $i \in I_1 \cap S_p$ is often composed as a weighted average of all of the control individuals, where the weights, $W(i, j)$, depend on the distance between p_i and p_j. In this analysis, however, I utilize a one-to-one matching technique known as nearest neighbor matching within a caliper. First, the data are randomly sorted and then treated students i are matched with a single non-treated student j such that the matched is defined by $\min_j = ||p_i - p_j||$ within a caliper of $.10\sigma_p$. In other words, I take a treated student and find a non-treated match who has the minimum difference in propensity to receive treatment within a caliper width of .10 standard deviations of the propensity score. If a match cannot be found, the observation is eliminated from the analysis. This kind of matching, often termed "nearest neighbor matching within a caliper," has become popular in the literature in instances of large sample sizes where multivariate analyses are used. Additionally, a caliper of $.25\sigma_p$ is often used; however, in this study, I use a smaller caliper due to the large size of my sample.[4]

More intuitively, this procedure finds an equivalent student *j* for every treated unit *i* whose propensity to receive treatment (enrolling full time) is nearly identical based on observable characteristics. In essence, I have created equivalent comparison groups between which we can gauge a less biased impact of full time enrollment. Any remaining bias in this procedure depends on whether there is a critical mass of information contained in ***x*** (Heckman et al., 1998). In order to overcome this bias, we must have confidence that the information contained in ***x*** is sufficient to establish independence between our desired outcome and the treatment. Given the richness of the dataset large number of covariates upon which I am able to match, I argue that I have satisfied this condition and that, to the extent that the array of covariates ***x*** captures all factors of bias towards enrolling full time, I will establish a unbiased relationship between full time enrollment and community college transfer.

[4] Results and discussion are presented only for the nearest neighbor algorithm due to its simplicity and intuitive nature. Additional strategies (e.g. kernel matching) were implemented and produced similar results. Additional information on types of matching can be founded in Smith and Todd (2005) as well as Guo and Fraser (2009).

Dataset and Variables

To complete this analysis, I make extensive use of a relatively underutilized, though rich, confidential, dataset: the Texas Schools Microdata Panel (TSMP). The TSMP is a restricted use administrative dataset that includes information on secondary school records from the Texas Education Administration (TEA) and post-secondary education outcomes from the Texas Higher Education Coordinating Board (THECB) from 1992 through 2010. Central to this project is providing a comprehensive and contemporary view of the role of the community college. The depth and breadth of information contained in the TSMP data system provides the opportunity to explore longitudinal studies with a rich set of covariates never before used to explain student success via the community college.

For the purpose of this analysis, I construct a sample of those students graduating from high school and immediately enrolling in the community college sector. In addition, I further limit the sample by including only those students who indicated their intent to complete a four-year degree.[5] I further condition on whether a student enrolls in an academic track as defined by the state. I follow four cohorts of students: those graduating from high school in 2000, 2001, 2002, and 2003. All of the analyses are performed for each cohort, separately, to provide a robustness check across cohorts.

I use a rich set of student characteristics to ascertain the propensity to enroll full time and categorize these factors revealed in the literature into four broad

[5] Considerable attention has been paid to the idea of the denominator—who to include in the sample—when calculating transfer/graduation rates. See Doyle (2009) for a summary.

categories: (1) race and sex, (2) pre-college academic preparation, (3), economic capacity, and (4) high school context. In addition, I condition on whether a student enrolled in academic course load at the community college, as defined by the state. Indicators for race (Lee & Frank, 1990) and sex (Surrette, 2001) are included as important covariates as suggested by extensive previous work.

Pre-college preparation is operationalized as important factors known to influence college success: enrollment in Advanced Placement (AP) coursework (Klopfenstien & Thomas, 2005) or International Baccalaureate (IB) coursework (Bailey & Karp, 2003), the completion of a trigonometry course (Adelman, 1999; Checkley, 2001; Tierney, Colyar, & Corwin, 2003; Long, Iatarola, & Conger, 2009), performance on the state math exam (Bound, Lovenheim, & Turner, 2009), and whether a student participated in a dual-enrollment program by earning college-level credits while still in high school (McCauley, 2007). The AP/IB indicator is coded as a dichotomy as 1 for students who successfully completed at least one AP or IB course in high school; the coding for the trigonometry indictor is similar, as is the indicator for having dual-enrolled during high school, and the state math score is kept at value, ranging from 0 to 60.

In terms of *economic capacity*, three measures are included: the state-defined free or reduced lunch indicator that the student was given in high school (Melguizo & Dowd, 2009), the county-level unemployment rate where the student attended high school (Niu & Tienda, 2011), and the wages earned while a student was simultaneously enrolled at the community college (Jepsen, Patel, & Troske, 2010).

High school context variables are also included: the pupil to teacher ratio (Lee & Smith, 1997), the overall enrollment (Lee & Smith, 1997), the percent minority (Black & Hispanic) (Fletcher & Tienda, 2010), and the high school urbanicity (as defined by the U.S. Census) (Fletcher & Tienda, 2010). Descriptive statistics are provided in Table 1.

Table 1:
Descriptive Statistics for Students Beginning at a Community College and Transfer Rates

Main Variables of Interest	2000		2001		2002		2003	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Transfer	0.3846	0.3846	0.3803	0.4855	0.3745	0.4840	0.3804	0.4855
12 Credits	0.7362	0.4407	0.7176	0.4502	0.7117	0.4530	0.7149	0.4515
CC Curriculum								
Academic Courseload	0.8282	0.3772	0.8204	0.3839	0.8067	0.3949	0.7813	0.4134
Race & Sex								
Hispanic	0.2565	0.4367	0.2804	0.4492	0.2701	0.4440	0.2920	0.4547
Black	0.0900	0.2862	0.0744	0.2624	0.0814	0.2734	0.0823	0.2748
Asian	0.0262	0.1598	0.0272	0.1628	0.0341	0.1815	0.0319	0.1758
Male	0.4673	0.4989	0.4549	0.4980	0.4690	0.4991	0.4662	0.4989
HS Academic Prep								
AP/IB Course	0.2897	0.4536	0.3018	0.4591	0.3044	0.4602	0.3269	0.4691
Trig Course	0.3109	0.4629	0.3283	0.4696	0.3367	0.4726	0.3569	0.4791
Math Score	47.3309	10.4626	49.1700	11.6295	49.0593	11.2648	43.3530	12.2187
Dual Enrollment	0.1250	0.3307	0.1713	0.3768	0.1802	0.3844	0.2111	0.4081
Economic Situation								
Economic Status	1,824	1,930	1,835	1,839	1,839	1,871	1,860	1,930
County Unemployment	0.1902	0.3925	0.2071	0.4052	0.1988	0.3991	0.2272	0.4190
Wages, Fall Term	4.4770	1.6068	4.9910	1.3065	6.2116	1.0532	6.6556	1.2715
High School Context								
HS Pupil:Teacher	14.5876	2.3352	14.5047	2.4589	14.8445	2.3441	14.8344	2.3101
HS Enrl	1,630	909	1,598	939	1,691	942	1,676	937
HS %Minority	0.4190	0.2815	0.4344	0.2903	0.4390	0.2805	0.4504	0.2919
HS PPE	3,975	444	4,149	494	4,304	530	4,302	549
HS Urbanicity	0.3441	0.4751	0.3638	0.4811	0.3851	0.4866	0.3830	0.4861
Observations (N)	15,328		13,395		14,391		16,160	

Independent Variable of Interest

The key independent variable is that of enrolling full time in the first semester at the community college. This variable is coded as a dichotomy with 0 for those students enrolling in 11 or less credits and 1 for those students enrolling in 12 or more. This definition of full time status stems from the federal government in that undergraduate students become eligible to receive federal financial aid in the form of Stafford loans by enrolling in 12 or more academic credits per semester. As an example of how credit-taking behavior varies by observed covariates, figures 1a, 1b, 1c, and 1d show how credit-taking patterns tend to be varied by race; Hispanic and Black students show larger densities in the six to nine credit region than other groups. The matching technique I use is designed to account for non-uninform distributions of the covariates in order to account for selection bias and move towards a less biased estimate of credit taking behavior on eventual transfer.

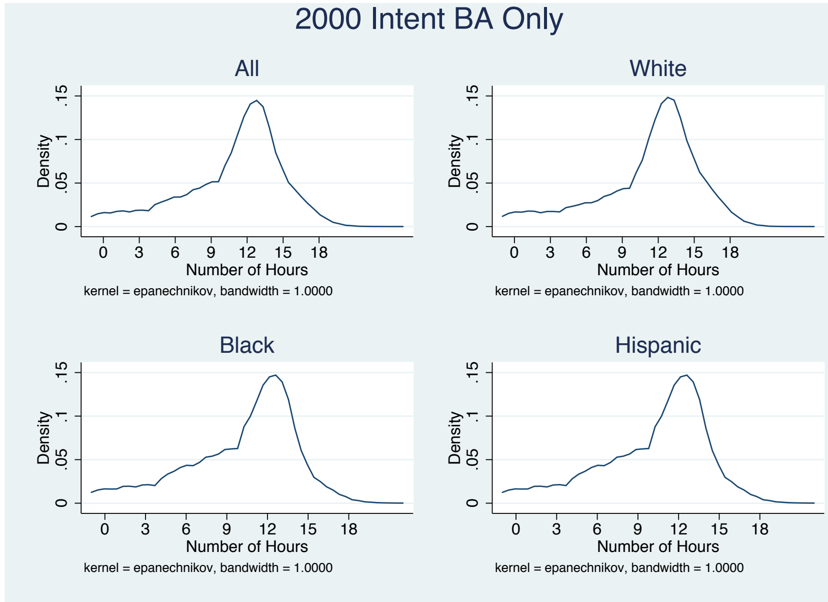

Figure 1a: Density Plot, by Race, for Credit Taking Behavior for Those Community College Students Intending to Earn a Bachelor's Degree, 2000

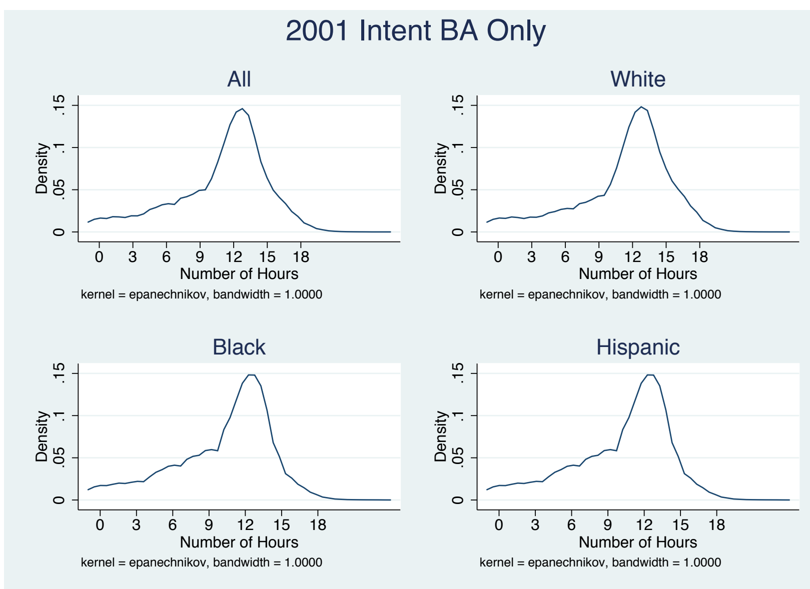

Figure 1b: Density Plot, by Race, for Credit Taking Behavior for Those Community College Students Intending to Earn a Bachelor's Degree, 2001

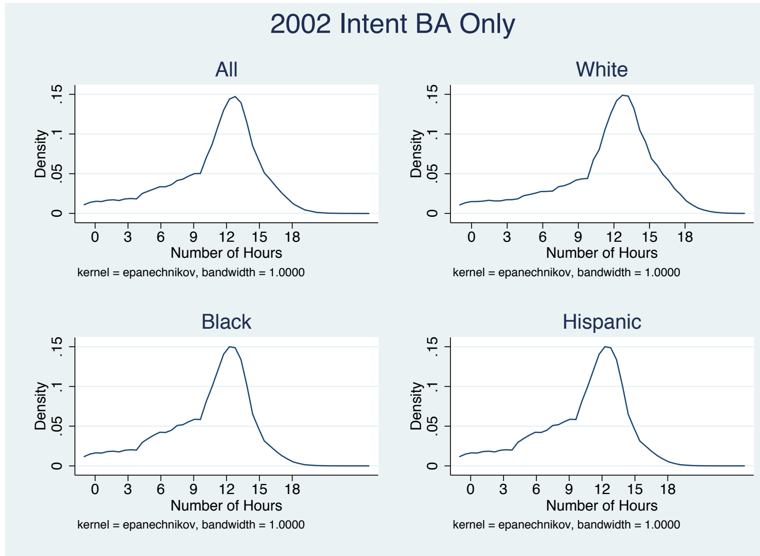

Figure 1c: Density Plot, by Race, for Credit Taking Behavior for Those Community College Students Intending to Earn a Bachelor's Degree, 2002

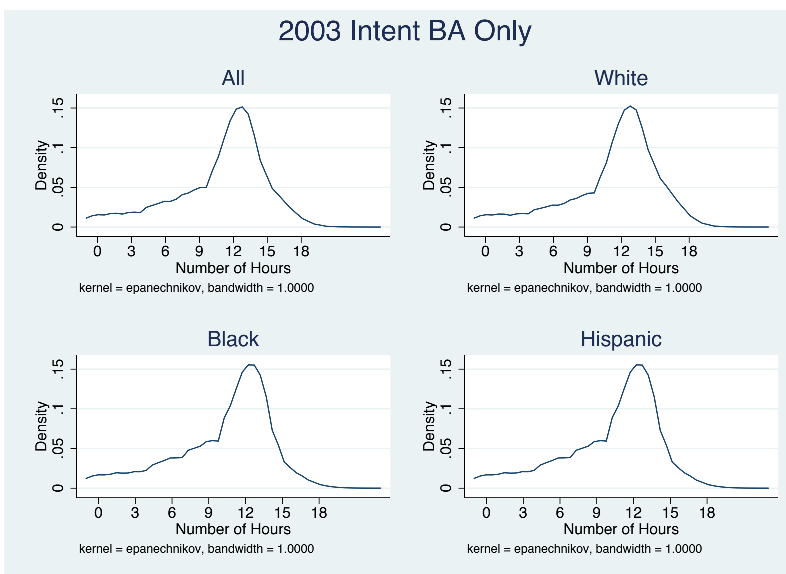

Figure 1d: Density Plot, by Race, for Credit Taking Behavior for Those Community College Students Intending to Earn a Bachelor's Degree, 2003

Dependent Variable

The dependent variable of interest is that of eventual transfer to a four-year institution. Using unique identification codes, students are tracked through the higher education system in Texas. Eventual transfer is coded as a dichotomy with 0 for those students who never appear in the enrollment files at a Texas four-year institution and 1 for those students who enroll in three or more credit hours in at least one fall or spring semester at any point in the six-year span following initial enrollment in the community college sector. For instance, those students beginning their studies at a community college are coded as having transferred if found in any four-year enrollment file up to, and including, Spring 2006. Mean transfer, by covariate, are provided in Table 2.

Table 2
Percentage of community college students who ever transfer, by attribute

	2000	2001	2002	2003
Overall				
Transfer	37.87%	37.52%	37.11%	37.51%
CC Curriculum				
12 Credits	42.24%	42.74%	42.31%	42.98%
Academic Courseload	39.38%	39.91%	39.27%	39.71%
Race				
Hispanic	28.97%	29.95%	28.48%	30.46%
Black	29.54%	29.00%	30.99%	29.01%
Asian	57.44%	49.04%	50.75%	55.57%
White	43.03%	42.10%	43.15%	42.78%
Male	36.32%	36.47%	35.28%	35.88%
Economic Situation				
Economic Status	26.99%	26.69%	25.44%	27.54%

Taken collectively, Figures 1a-1d and Table 2 demonstrate the need for the use of a counterfactual framework—there exists observable differences shown to be related to both a student's likelihood to enroll full time and successfully transfer. Figure 1 illustrates how enrollment behavior is not uniform by race, with Hispanic and Black students enrolling full-time at lower percentages than White students. In Table 2, this same characteristic is related to eventual transfer, with Hispanic and Black students transferring at lower rates. Thus, any comparison not taking into account these important factors would be subject to over-reporting the impact of full-time enrollment on eventual transfer. By including information about race as well as sex, pre-college academic preparation, economic capacity, and high school context, I seek to provide an unbiased estimate to inform both policy and the research community. What follows are results from the propensity score analysis.

Results

Matching Results

The naïve estimator would compare the mean transfer rates between those who enrolled full time and those who did not. Instead, however, I seek to establish a counterfactual group free from self-selection bias by using a matching technique. Important in the matching technique is the initial analysis to determine each individual's propensity to be a member of the treated group. In order to determine an individual's propensity to enroll full-time, I conducted a probit with the selection variables. Table 3 shows the results from this regression. As originally suggested in the density plots, and as confirmed by the probit analysis, Hispanic students are less likely to enroll full time. In addition, I find consistently positive and statistically significant relationships for academic coursework in the community college as well as academic preparation while in high school.

Table 3

Probit Results; Outcome: Enrolling full time

	2000		2001		2002		2003	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
CC Curriculum								
Academic Courseload	0.447	(.028) **	0.524	(.029) **	0.471	(.028) **	0.340	(.025) **
Race & Sex								
Hispanic	-0.250	(.034) **	-0.089	(.035) *	-0.095	(.033) **	-0.084	(.032) **
Black	-0.029	(.042)	0.056	(.048)	-0.138	(.043) **	-0.019	(.042)
Asian	-0.279	(.069) **	-0.233	(.072) **	-0.297	(.062) **	-0.192	(.061) **
Male	-0.005	(.023)	-0.062	(.024) **	-0.038	(.023) +	-0.026	(.022)
HS Academic Prep								
AP/IB Course	0.104	(.028) **	0.142	(.029) **	0.034	(.027)	0.096	(.025) **
Trig Course	0.245	(.028) **	0.237	(.028) **	0.222	(.027) **	0.187	(.025) **
Math Score	0.008	(.001) **	0.005	(.001) **	0.006	(.001) **	0.005	(.001) **
Dual Enrollment	0.022	(.037)	0.051	(.035)	0.118	(.033) **	0.062	(.029) *
Economic Situation								
Economic Status	0.127	(.034) **	0.126	(.036) **	-0.004	(.033)	0.001	(.03)
County Unemployment	0.056	(.009) **	0.030	(.01) **	-0.012	(.011)	0.023	(.009) *
Wages, Fall Term	0.000	(.) **	0.000	(.) **	0.000	(.) **	0.000	(.) **
High School Context								
HS Pupil:Teacher	0.020	(.007) **	-0.021	(.007) **	-0.007	(.007)	-0.018	(.007) **
HS Enrl	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)
HS %Minority	-0.100	(.058) +	-0.205	(.06) **	-0.186	(.055) **	-0.296	(.053) **
HS PPE	0.000	(.) **	0.000	(.) +	0.000	(.) **	0.000	(.)
HS Urbanicity	-0.158	(.028) **	-0.095	(.029) **	-0.085	(.027) **	0.011	(.026)
Constant	-0.780	(.189) **	-0.052	(.202)	-0.076	(.206)	0.267	(.178)
Log Likelihood		-8369.06		-7547.04		-2163.38		-9282.53
Chi2		949.13		851.96		49.47		754.23
N		15,328		13,395		14,391		16,160

**p < 0.05, **p < 0.01, +p < 0.10*

From Table 3, we learn the sign and relative magnitude of the influence of the covariates as well as their statistical significance. It is difficult, however, to capture an easily comprehensible effect of the covariates without computing a few predicted probabilities. To better understand the effect of the selection variables, I create profiles of students and use the estimated coefficients to determine a predicted probability of taking enrolling full time. For instance, in 2000, a Hispanic male from an economically disadvantaged family background and lacking advanced academic preparation in high school (with mean values on the other covariates) has a predicted 64% of enrolling full-time. The same student, however, with strong academic preparation in high school has a predicted 81% probability of enrolling full-time.[6] An example of these calculations is provided in the appendix.

The matching procedure uses the propensity score to match every treated student with only one non-treated student with a very nearly identical likelihood of enrolling full-time, based on the selection variables. For example, a female Hispanic student who is academically prepared for college and enrolls full time in her first semester is compared only with a student who has the same propensity to enroll full time based on the observable characteristics, yet did not do so. This process is repeated for every treated student in the dataset. If a match cannot be found, the record is discarded. The goal of this process is to establish a treatment and control group that are statistically indistinguishable in terms of the relationship of student characteristics to credit taking behavior. Table 4 presents t-statistics from logistic regression results from binary analyses of the student covariates and enrolling full time, for both the unmatched and matched datasets.

[6] Predicted probabilities for probit regression results are provided in the appendix. A student who lacks academic preparation in high school is defined as having not taking an AP/IB course or trigonometry course and scoring two standard deviations below the mean on the state math exam. A student with advanced academic preparation has taken both an AP/IB course and a trigonometry course and scored at the mean on the math exam.

Table 4

T-tests for differences in means for students above and below full time status

	2000		2001		2002		2003	
	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched
CC Curriculum								
Academic Courseload	19.62	-0.183	21.145	-0.767	20.963	0.508	16.689	-0.496
Race & Sex								
Hispanic	-11.242	0.718	-7.664	1.278	-9.55	-0.137	-9.779	0.169
Black	-1.404	-0.93	-0.785	0.69	-3.914	0.056	-3.189	1.454
Asian	-2.845	0.728	-3.066	-1.186	-2.954	1.385	-2.712	0.137
Male	0.062	1.856	-3.522	-1.594	-1.943	1.561	-2.125	0.23
HS Academic Prep								
AP/IB Course	10.623	-0.354	11.032	0.289	8.307	0.772	10.266	0.082
Trig Course	15.898	0.8	13.924	-1.276	14.201	-1.091	13.539	0.161
Math Score	14.128	0.903	10.525	0.487	11.874	0.333	12.308	-0.501
Dual Enrollment	5.963	1.299	8.373	-0.812	9.859	0.683	9.11	-0.773
Economic Situation								
Economic Status	-3.381	-0.112	-2.335	1.764	-6.931	1.12	-6.8	1.317
County Unemployment	5.921	-0.711	2.06	0.532	-2.048	0.284	1.069	-0.964
Wages, Fall Term								
High School Context	-13.211	-0.734	-12.08	-1.407	-12.62	-0.714	-11.333	0.072
HS Pupil:Teacher	-4.412	2.002	-8.402	-0.95	-6.846	-0.31	-8.453	-0.447
HS Enrl	-4.85	2.215	-6.103	-0.903	-5.497	-0.589	-8.431	0.102
HS %Minority	-7.408	0.664	-8.026	1.271	-9.332	-0.84	-12.248	-1.577
HS PPE	2.281	-0.318	3.674	0.04	3.552	-1.288	3.727	0.299
HS Urbanicity	-10.81	0.84	-8.43	1.18	-9.46	0.67	-8.17	0.46

In the unmatched samples, nearly all of the selection variables are statistically significant at the 95% confidence level. Such a strong correlation between these characteristics in ***x*** and the treatment (enrolling full-time) can produce bias in any estimate of the treatment. In all of the years, however, this fades in the matched sample (with the exception of two covariates in 2000), suggesting no major statistically significant differences between the treatment and control groups. Thus, I argue that I have achieved equivalent treatment and control groups and, to the extend that these covariates capture the propensity to receive treatment, may proceed with a treatment analysis to determine an unbiased effect of full time enrollment in the first semester on eventual transfer to a four-year institution.

Treatment Results

Once an equivalent control group has been established, I use a weighted logistic regression analysis to ascertain the effect of full time enrollment. Specifically, all treated students are given a weight of 1 and matched control students are weighted by a factor of n_1/n_0 where n_1 is the number of students in the treated subclass $(I_1 \cap S_p)$ and n_0 is the number of students in the control subclass. This approach guarantees that control students (of which not all are used) receive no more weight than treated students (Ho et al., 2005). The results for the treatment analysis indicate a positive effect, in both the unmatched and matched samples, for enrolling full time on eventual transfer. Detailed results are provided in Table 5 and demonstrate that although the coefficient on enrolling full time is smaller in the matches samples, the positive effect of enrolling full time does not vanish after taking into account potential bias. In 2000, the estimated effect of full time enrollment in the unmatched sample is 0.92, with a 95% confidence interval from 0.84 to 1.00. This translates to a mean difference in the transfer rate between those above and below full-time status of 20%, with a 95% confidence interval from about 18% to 22%. In the same year, the matched sample has an estimated coefficient of .79, 95% confidence interval from 0.65 to .92. This translates to a mean difference in the transfer rate between those enrolling full time and those who did not of 17.4%, with a 95% confidence interval from about 14% to 20%.[7] This pattern, though possessing a slight dip in 2001, is consistent across all years. Figure

[7] Detailed calculations of these percentages can be found in the Appendix.

2 provides a comparison of the estimated effect of full time enrollment for both matched and matched samples, across all years, with mean differences highlighted and confidence intervals shaded.

Table 5

Maximum likelihood estimates for the impact of full time status on transfer

	2000		2001		2002		2003	
	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched
Intercept	-1.19	-1.08	-1.12	-0.84	-1.11	-1.01	-1.12	-0.98
	(.03)	(.05)	(.04)	(.05)	(.03)	(.05)	(.03)	(.04)
Full time status	0.92	0.79	0.83	0.51	0.81	0.66	0.85	0.67
	(.04)	(.07)	(.04)	(.07)	(.04)	(.05)	(.04)	(.06)
Log Likelihood	-10983.83	-2567.74	-9570.56	-2163.38	-10561.46	-2334.47	-11442.27	-3321.81
Chi2	593.66	139.90	445.22	49.47	475.01	89.33	561.84	129.95
N	15,328	4,110	13,395	3,352	14,391	3,708	16,160	5,238

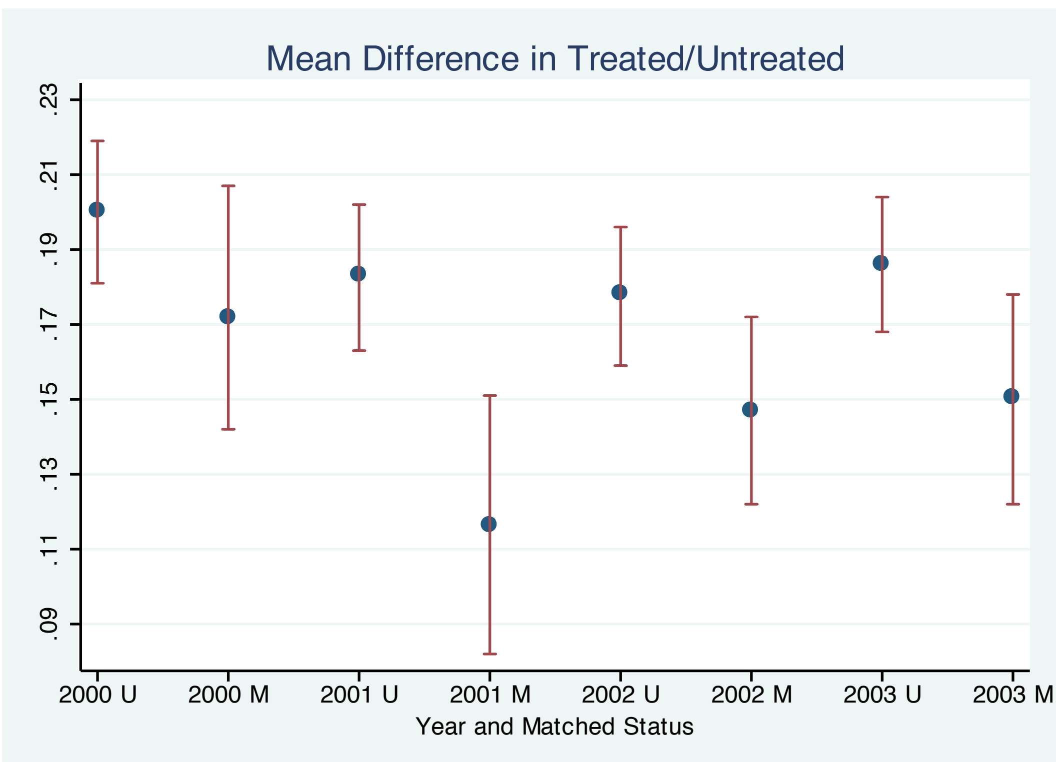

Figure 2: Mean differences in treated/untreated groups, Matched and unmatched samples for full time status and transfer outcome

Sensitivity Analysis

Next, I discuss a sensitivity analysis designed to assess the bias of the ATT estimate outlined above. This type of sensitivity analysis is recommended to accompany any propensity score matching technique (Ichino, Mealli, & Nannicini, 2008) and assesses the sensitivity of the ATT estimate in a simulation where there may be an unobserved factor determining placement into either the treatment or control group. Imagine an unobserved covariate, say, motivation, that is correlated with both the selection into treatment (enrolling full time) and successful transfer. Although I have established equivalent treatment and control groups based on the observables, by failing to account for this factor, any estimate of the impact of enrolling full time would be biased. It would appear as though enrolling full time had a stronger impact on transfer than would have occurred if I were able to control for a covariate such as motivation. While failing to account for unobservable factors such as motivation has plagued educational research, bringing many results into question, the sensitivity analysis proposed by Ichino, Mealli, and Nannicini (2008) seeks to identify how severe this factor would need to be in order to bias results. First, I simulate an unobserved covariate that mimics the set of covariates I already have (i.e. race, sex, and high school preparation in its magnitude and presence in the sample, yet is uncorrelated with observable characteristics. If, after accounting for this unobserved variable, I remain able to obtain statistically significant, positive results, I can safely conclude that to the extent to which I have accounted the selection bias, there exists a true relationship between full time enrollment and transfer. What follows is a more complete theoretical description of this procedure.

Although I have tested for equivalent treatment and control groups by regressing the selection variables, $\boldsymbol{x}$, on the treatment variable z, based on the work of Rosenbaum and Rubin (1983) and Ichino, Mealli, and Nannichini (2008), suppose that the assignment to treatment is not unconfounded with the observable variables. Additionally, suppose that there exists a binary covariate, u, that is associated with both the treatment and the outcome. In other words, suppose that:

$$\Pr(z=1 \mid y_0, y_1, x) \neq \Pr(z=1 \mid x)$$

Furthermore, suppose that, given an unobserved binary covariate u:

$$\Pr(z=1 \mid y_0, y_1, x, u) = \Pr(z=1 \mid x, u)$$

The sensitivity analysis assesses the point estimates for the ATT under the propensity score matching technique by imposing values of the factors that determine u and then using a predicted value of u for each of the treated and control students to re-estimate the ATT using the predicted u. By changing the specification of u, I am able to assess the robustness of the ATT estimate under different hypotheses about the unobserved confounder. Furthermore, I am able to determine if there is a hypothesis about u that could drive the ATT to zero. However, if the findings for ATT under multiple hypotheses are consistent, unbiased inference becomes more concrete (Ichino, Mealli, & Nannichini, 2008).

Specifically, consider the case of $y_0, y_1 \in \{0,1\}$ where $y = z \times y_1 + (1 - z) \times y_0$ represents the observed outcome for a given student and treatment/control classification. In this situation, I characterize the distribution of u such that:

$$\Pr(u{=}1 \mid z{=}i, y{=}j, x) = \Pr(u{=}1 \mid z{=}i, y{=}j) \equiv p_{ij}$$

Just as $y_0, y_1 \in \{0,1\}$, establish $i, j \in \{0,1\}$. I then learn the probability p_{ij} in each of the four categorizations established by combinations of the treatment and outcome values. By using different specifications of p_{ij} I can attribute different values of u to each of the students in both the treatment and control groups. Then, I treat u as any other selection variable used in the creation of the propensity score and the resulting ATT estimate. By repeating this estimation many (1,000) times, I can obtain an ATT estimate that is robust to different specifications of the unobserved variable u. Such an estimate is consequently free from bias of any underlying observed variable.

As Ichino, Mealli, and Nannicini (2008) demonstrate, any threat to the ATT estimate would arise from the situation where u has both a positive effect on the control group outcome (where $p_{01} - p_{00} > 0$, an "outcome effect") and the selection into the treatment (where $p_{1*} - p_{0*} > 0$, a "selection effect"). Thus, I am able to interpret the results from the sensitivity analysis by focusing on confounders that produce this outcome. To gauge the magnitude of bias caused by u, I calculate the outcome effect as an average of the odds ratios from logistic regression model of $\Pr(y{=}1 \mid z{=}0, u, x)$ as:

$$\frac{\dfrac{\Pr(y{=}1 \mid z{=}0, u{=}1, x)}{\Pr(y{=}0 \mid z{=}0, u{=}1, x)}}{\dfrac{\Pr(y{=}1 \mid z{=}0, u{=}0, x)}{\Pr(y{=}0 \mid z{=}0, u{=}0, x)}} \equiv \Gamma$$

Then, to gauge the magnitude of bias caused by u, I calculate the selection effect as an average of the odds ratios from logistic regression model of $\Pr(z{=}1 \mid u, x)$ as:

$$\frac{\Pr(z=1 \mid u=1, x) \,/\, \Pr(z=0 \mid u=1, x)}{\Pr(\mathrm{z}=1 \mid u=0, x) \,/\, \Pr(z=0 \mid u=0, x)} \equiv \Lambda$$

Estimates for Γ and Λ, above as well as the ATT estimates produced under these scenarios will allow me to determine whether the original ATT estimates generated from the propensity score matching technique (that is, the estimates where *u* is not included) are robust to different specifications of an underlying variable. In the most simple case, I set p_{ij} equal to 0.50 for all *i* and *j* combinations to simulate a "neutral" confounder. I then simulate p_{ij} to mimic the set of selection variables. For example, if 45% of the students who enrolled full-time and successfully transferred are male, I set p_{11} equal to 0.45 and similarly for the other covariates and p_{ij} values. Taken collectively, the ATT estimates produced under these various parameterizations of p_{ij} will shed light on the robustness of the original ATT estimates.

Results from the Sensitivity Analysis

First, I establish a neutral confounder and then construct confounders to mimic the observed covariates of Hispanic, Black, Asian, male, and economic disadvantage. Each row of the tables contains the four probabilities $p_{\mathrm{ij}} = \Pr(U = 1 \mid z = i, y = j)$ with $i, j \in \{0,1\}$ that determine the distribution of the unobserved covariate (say, motivation) under which the ATT is estimated. Tables 6a – 6d show the results from the sensitivity analysis. The first row presents the ATT estimate without any confounders[8] and the second row contains a neutral confounder where $p = .5 \; \forall \; i, j$. The remaining rows in the tables represent estimates for the ATT calculated under conditions where the distribution of u is comparable to the distribution of observed variables.

Table 6a

Sensitivity analysis for the impact of full time status on transfer, 2000

	Fraction U=1 by treatment/outcome							
	p11	p10	p01	p00	Outcome Effect (Γ)	Selection Effect (Λ)	ATT	SE
No confounder	0.00	0.00	0.00	0.00	--	--	0.157	0.012
Neutral Confounder	0.50	0.50	0.50	0.50	1.0	1.0	0.153	0.013
Confounder-like								
Hispanic	0.19	0.27	0.25	0.35	0.6	0.7	0.146	0.014
Black	0.07	0.11	0.09	0.10	0.9	0.9	0.154	0.013
Asian	0.04	0.02	0.07	0.02	3.5	0.7	0.155	0.013
Male	0.45	0.48	0.42	0.48	0.8	1.0	0.153	0.013
Econ	0.13	0.23	0.16	0.23	0.6	0.9	0.152	0.013

Table 6b

Sensitivity analysis for the impact of full time status on transfer, 2001

	Fraction U=1 by treatment/outcome							
	p11	p10	p01	p00	Outcome Effect (Γ)	Selection Effect (Λ)	ATT	SE
No confounder	0.00	0.00	0.00	0.00	--	--	0.119	0.013
Neutral Confounder	0.50	0.50	0.50	0.50	1.0	1.0	0.117	0.015
Confounder-like								
Hispanic	0.21	0.30	0.27	0.35	0.7	0.8	0.118	0.015
Black	0.05	0.09	0.08	0.08	1.1	1.0	0.114	0.014
Asian	0.03	0.02	0.05	0.03	1.6	0.7	0.109	0.013
Male	0.43	0.45	0.46	0.48	0.9	0.9	0.118	0.015
Econ	0.14	0.25	0.18	0.24	0.7	0.9	0.117	0.014

[8] This ATT estimate is similar, though not precisely the same as the previously estimated ATT estimate. This sensitivity analysis uses a different random sorting of the data. Results from the different sortings are very similar.

Table 6c

Sensitivity analysis for the impact of full time status on transfer, 2001

	Fraction U=1 by treatment/outcome							
	p11	p10	p01	p00	Outcome Effect (Γ)	Selection Effect (Λ)	ATT	SE
No confounder	0.00	0.00	0.00	0.00	--	--	0.147	0.012
Neutral Confounder	0.50	0.50	0.50	0.50	1.0	1.0	0.140	0.014
Confounder-like								
Hispanic	0.20	0.29	0.25	0.35	0.6	0.7	0.134	0.014
Black	0.06	0.09	0.10	0.10	1.1	0.8	0.140	0.014
Asian	0.05	0.03	0.08	0.04	2.1	0.8	0.142	0.014
Male	0.44	0.47	0.44	0.49	0.8	0.9	0.138	0.014
Econ	0.13	0.24	0.19	0.26	0.7	0.8	0.136	0.014

Table 6d

Sensitivity analysis for the impact of full time status on transfer, 2003

	Fraction U=1 by treatment/outcome							
	p11	p10	p01	p00	Outcome Effect (Γ)	Selection Effect (Λ)	ATT	SE
No confounder	0.00	0.00	0.00	0.00	--	--	0.141	0.011
Neutral Confounder	0.50	0.50	0.50	0.50	1.0	1.0	0.141	0.013
Confounder-like								
Hispanic	0.23	0.31	0.28	0.37	0.7	0.7	0.137	0.013
Black	0.06	0.09	0.09	0.10	0.9	0.9	0.142	0.013
Asian	0.05	0.02	0.07	0.03	2.4	0.8	0.146	0.012
Male	0.44	0.47	0.43	0.49	0.8	0.9	0.141	0.013
Econ	0.17	0.26	0.18	0.30	0.5	0.8	0.138	0.013

Overwhelmingly, the ATT estimates remain consistent, even after the introduction of confounders. In only four instances (2000: Hispanic; 2001: Asian; and 2002: Hispanic, Econ) does the ATT estimate differ by more than one percentage point from the baseline estimate. In no instance does the ATT estimate differ by more than two percentage points from the baseline estimate. Taken collectively, these results convey a strong impression of robustness of the baseline estimate.

Killer Confounders

Next, I push the sensitivity analysis one step further as suggested by Ichino, Mealli, and Nannicini (2008) to determine so-called "killer" confounders—parameterizations of u such that the ATT estimate is driven to zero. First, however, understand the meaning of such a "killer" confounder. Recall that:

$$\text{ATT} = E(y_1 \mid z=1) - E(y_0 \mid z=1)$$

As aforementioned, y_0 is not observed when $z = 1$ and, thus, the term $E(y_0 \mid z=1)$ cannot be estimated from the available data. It is possible, however, to establish non-parametric bounds for the ATT estimate by substituting $E(y_0 \mid z=1)$ with its largest and smallest obtainable values:

$$E(y_1 \mid z=1) - 1 \leq \text{ATT} \leq E(y_1 \mid z=1)$$

Furthermore, establish the difference d as $d = p_{01} - p_{00}$ (an unconditioned estimate of the effect of u on the control students successfully transferring) and the difference s as $s = p_{1*} - p_{0*}$ (an unconditioned estimate of the effect of u on assignment into treatment). Thus far, I have fixed both s and d to be zero; however, by varying these terms along with the associated Γ and Λ terms, I am able to ascertain how severe the impact of u would need to be on the outcome effect and/or the treatment effect in order to produce a substantially biased ATT estimate. In other words, I am able to determine how strong the effects of u on either treatment and/or outcome would need to be in order to “kill” the ATT estimate. What follows are the results from this analysis of “killer” confounders.

Killer Confounder Results

Tables 7a – 7d present the results of the killer confounders, by year. In each table, d (the effect of the confounder on transfer) and s (the effect of the confounder on assignment into treatment) are varied from 0.1 to 0.7 along the rows and columns, respectively. Overall, the ATT estimates remain positive and statistically significant until both the effect on transfer and the effect on treatment sizeable values. Indeed, the estimate for 2002 varies only by 3 percentage points for all simulations of assignment into treatment (s=0.1 to .07) for low levels of the effect on transfer (d=0.1). Additionally, the estimate approaches zero only for values of s and d greater than 0.5. More intuitively, these results show that only under extreme values (where an unobserved factor has a sizeable effect on both selection into treatment and eventual transfer) will the estimates of the effect of full time enrollment on transfer approach zero. Put differently, it would take a substantial confounder to “kill” the estimates.

Table 7a:
Killer Confounder Analysis for the Impact of Full Time Status on Transfer, 2000

		s						
		0.1	0.2	0.3	0.4	0.5	0.6	0.7
d	0.1	0.155	0.151	0.150	0.144	0.139	0.130	0.127
		(0.011)	(0.012)	(0.012)	(0.014)	(0.019)	(0.021)	(0.022)
	0.2	0.153	0.147	0.137	0.127	0.119	0.103	0.099
		(0.013)	(0.015)	(0.015)	(0.017)	(0.019)	(0.022)	(0.028)
	0.3	0.151	0.143	0.133	0.122	0.111	0.096	0.079
		(0.014)	(0.015)	(0.016)	(0.018)	(0.020)	(0.024)	(0.028)
	0.4	0.147	0.129	0.112	0.090	0.067	0.041	0.005
		(0.014)	(0.014)	(0.016)	(0.018)	(0.021)	(0.023)	(0.028)
	0.5	0.143	0.120	0.096	0.065	0.034	-0.012	-0.063
		(0.014)	(0.014)	(0.016)	(0.018)	(0.020)	(0.024)	(0.027)
	0.6	0.140	0.110	0.076	0.037	-0.003	-0.053	-0.053
		(0.014)	(0.014)	(0.016)	(0.018)	(0.020)	(0.044)	(0.047)
	0.7	0.141	0.101	0.059	0.012	-0.037	-0.049	-0.062
		(0.014)	(0.014)	(0.016)	(0.018)	(0.030)	(0.042)	(0.046)

Table 7b:
Killer Confounder Analysis for the Impact of Full Time Status on Transfer, 2001

		s						
		0.1	0.2	0.3	0.4	0.5	0.6	0.7
d	0.1	0.117	0.114	0.113	0.109	0.105	0.098	0.096
		(0.015)	(0.016)	(0.016)	(0.019)	(0.026)	(0.029)	(0.030)
	0.2	0.115	0.111	0.103	0.096	0.090	0.078	0.075
		(0.018)	(0.020)	(0.020)	(0.023)	(0.026)	(0.030)	(0.038)
	0.3	0.114	0.108	0.100	0.092	0.084	0.072	0.060
		(0.019)	(0.020)	(0.022)	(0.025)	(0.027)	(0.033)	(0.038)
	0.4	0.111	0.097	0.084	0.068	0.051	0.031	0.004
		(0.019)	(0.019)	(0.022)	(0.025)	(0.029)	(0.031)	(0.038)
	0.5	0.108	0.091	0.072	0.049	0.026	-0.009	-0.048
		(0.019)	(0.019)	(0.022)	(0.025)	(0.027)	(0.033)	(0.037)
	0.6	0.106	0.083	0.057	0.028	-0.002	-0.040	-0.040
		(0.019)	(0.019)	(0.022)	(0.025)	(0.027)	(0.060)	(0.064)
	0.7	0.106	0.076	0.045	0.009	-0.028	-0.037	-0.047
		(0.019)	(0.019)	(0.022)	(0.025)	(0.041)	(0.057)	(0.063)

Table 7c:
Killer Confounder Analysis for the Impact of Full Time Status on Transfer, 2002

		s						
		0.1	0.2	0.3	0.4	0.5	0.6	0.7
d	0.1	0.144	0.140	0.139	0.134	0.129	0.121	0.118
		(0.017)	(0.019)	(0.019)	(0.022)	(0.029)	(0.032)	(0.034)
	0.2	0.142	0.137	0.127	0.118	0.111	0.096	0.092
		(0.020)	(0.023)	(0.023)	(0.026)	(0.029)	(0.034)	(0.043)
	0.3	0.140	0.133	0.124	0.113	0.103	0.089	0.073
		(0.022)	(0.023)	(0.025)	(0.028)	(0.031)	(0.037)	(0.043)
	0.4	0.137	0.120	0.104	0.084	0.062	0.038	0.005
		(0.022)	(0.022)	(0.025)	(0.028)	(0.032)	(0.036)	(0.043)
	0.5	0.133	0.111	0.089	0.060	0.032	-0.011	-0.059
		(0.022)	(0.022)	(0.025)	(0.028)	(0.031)	(0.037)	(0.042)
	0.6	0.130	0.102	0.071	0.034	-0.003	-0.049	-0.049
		(0.022)	(0.022)	(0.025)	(0.028)	(0.031)	(0.068)	(0.073)
	0.7	0.131	0.094	0.055	0.011	-0.034	-0.046	-0.058
		(0.022)	(0.022)	(0.025)	(0.028)	(0.046)	(0.065)	(0.071)

Table 7d:
Killer Confounder Analysis for the Impact of Full Time Status on Transfer, 2003

		s						
		0.1	0.2	0.3	0.4	0.5	0.6	0.7
d	0.1	0.120	0.117	0.116	0.111	0.108	0.101	0.098
		(0.019)	(0.021)	(0.021)	(0.024)	(0.033)	(0.036)	(0.038)
	0.2	0.118	0.114	0.106	0.098	0.092	0.080	0.077
		(0.022)	(0.026)	(0.026)	(0.029)	(0.033)	(0.038)	(0.048)
	0.3	0.117	0.111	0.103	0.094	0.086	0.074	0.061
		(0.024)	(0.026)	(0.028)	(0.031)	(0.035)	(0.041)	(0.048)
	0.4	0.114	0.100	0.087	0.070	0.052	0.032	0.004
		(0.024)	(0.024)	(0.028)	(0.031)	(0.036)	(0.040)	(0.048)
	0.5	0.111	0.093	0.074	0.050	0.026	-0.009	-0.049
		(0.024)	(0.024)	(0.028)	(0.031)	(0.035)	(0.041)	(0.047)
	0.6	0.108	0.085	0.059	0.029	-0.002	-0.041	-0.041
		(0.024)	(0.024)	(0.028)	(0.031)	(0.035)	(0.076)	(0.081)
	0.7	0.109	0.078	0.046	0.009	-0.029	-0.038	-0.048
		(0.024)	(0.024)	(0.028)	(0.031)	(0.052)	(0.073)	(0.079)

Discussion

Enrolling full time in the first semester at a community college has a significant positive effect on transfer to a four-year university. Furthermore, this finding is present after reducing inherent sample selection bias to which any study of this nature is prone. In addition, the sensitivity analysis reveals that these results appear to be robust against confounding factors and are threatened only by the presence of so-called "killer-confounders" that would have an extreme impact on the behavior of community college students. The magnitude of the "killer confounders" I have identified is greater than that of many factors often explored in the literature including part-time faculty (Jacoby, 2006), institutional enrollment and the percentage of enrolled minority students (Calcagno et al., 2008), as well as student behavioral characteristics (Hawley & Harris, 2006). This benefit of increased academic intensity in the first semester is consistent with the findings of Adelman (1994, 2004, 2006) and Doyle (2008), giving further support that by increasing student credit load to full time status, we will likely see increases in college student success.

Furthermore, these results suggest a positive relationship between engagement (as defined by full-time enrollment) and student success (as defined by transfer to a four-year institution). Student engagement theory (Kuh, 2001) suggests that students who are more engaged will experience higher levels of academic success. Additionally, pervious work has shown that full-time status typically results in higher levels of engagement (Kuh, 2005). Thus, by increasing student engagement by way of promoting full-time status, we should expect to see an increase in the transfer rates for community college students. From a policy perspective, this finding seems to give credence to the handful of states that have enacted policy to encourage, incentivize, or require full time enrollment in the community college sector.

Limitations

This study is subject to at least two limitations. First, financial aid information, a factor known to influence student success, is not include in the model due to data limitations at the time of the analysis. Future analyses would benefit from the inclusion of such data. Second, this study is limited in scope to data from the state of Texas, yet the results gleaned from this analysis are externally valid in at least three ways. First, Texas has a sizeable college-going population and has been highly active in its expansive in the community college sector, a trend also found nationally. Second, Texas has a diverse demographic composition and, in many ways, mirrors projections of the national racial composition. Finally, Texas has a varied landscape of institutions of higher education. Texas provides an excellent laboratory in which to study the community college given its sizeable college-going population, its increasing capacity in the two-year sector, and its shifting demographics.

The student unit record dataset in Texas provides the opportunity to expand upon the existing body of knowledge and tap a vast wealth of previously unexplored factors. Furthermore, the TSMP data in Texas provides the opportunity to conduct analyses over several cohorts through recent years. Given the ever-changing landscape of the community college sector, this level of information is essential to understanding the complex role of the community college. With a rising community college sector enrollment and recent policy changes geared at increasing student success, as well as significant social, political, and economic shifts within its borders, Texas stands to become a pioneer in terms of practices and policies related to the community college.

Contributions and Conclusions

This analysis of community college transfer is particularly timely given the recent community college summit at the White House in early October 2010 where President Obama reinforced public faith in the community college as an important pathway to an undergraduate degree. With such an increased focus on community college and far too few students attaining an undergraduate degree, it is paramount that we better understand the role of the community college so as to better inform research, policy, and practice. Policy related to credit load might be a key lever for student success and institutions as well as state systems are wise to look to this arena as a way promoting student transfer from community colleges. Full time status has been shown to positively influence successful transfer and other states have investigated mechanisms to encourage, incentivize, or require full time enrollment. While require full time status may appear like a grand idea at initial consideration, it may very well serve to decrease access to higher education as this may simply not be an option for many students. Instead, it seems more appropriate that next steps taken by states in the form of policy initiatives should, at the very least, encourage full time enrollment and perhaps offer various forms of incentives as well.

Appendix

Calculation of Predicted Probabilities

Probit Results; Outcome: Taking 12 or more credits

	2000			Pred. Prob. 1		Pred. Prob.2	
	Coef	SE		Value	Value*Coef	Value	Value*Coef
CC Curriculum							
Academic Courseload	0.447	(.028)	**	1	0.447	1	0.447
Race & Sex							
Hispanic	-0.250	(.034)	**	1	-0.250	1	-0.250
Black	-0.029	(.042)		0	0.000	0	0.000
Asian	-0.279	(.069)	**	0	0.000	0	0.000
Male	-0.005	(.023)		1	-0.005	1	-0.005
HS Academic Prep							
AP/IB Course	0.104	(.028)	**	0	0.000	1	0.104
Trig Course	0.245	(.028)	**	0	0.000	1	0.245
Math Score	0.008	(.001)	**	26.406	0.216	47.331	0.388
Dual Enrollment	0.022	(.037)		0.000	0.000	1.000	0.022
Economic Situation							
Economic Status	0.127	(.034)	**	1.0	0.127	1.0	0.127
County Unemployment	0.056	(.009)	**	4.474	0.251	4.474	0.251
Wages, Fall Term	0.000	(.)		1823.968	-0.117	0.000	0.000
High School Context							
HS Pupil:Teacher	0.020	(.007)	*	14.450	0.283	14.450	0.283
HS Enrl	0.000	(.)		1615.968	-0.022	1615.968	-0.022
HS %Minority	-0.100	(.058)		0.438	-0.044	0.438	-0.044
HS PPE	0.000	(.)	**	3977.804	0.332	3977.804	0.332
HS Urbanicity	-0.158	(.028)	**	0.350	-0.055	0.350	-0.055
Constant	-0.780	(.189)	**	1.0	-0.780	1.0	-0.780
Log Likelihood		-8477.210					
Chi2		843.56					
N		15,425		SUM	0.382	SUM	1.041
				Pred. Prob	64.1%	Pred Prob	81.3%

**p < 0.05, **p < 0.01, +p < 0.10*

Predicted Probabilties are calculated by summing the values and determining the location on the Normal curve.

Calculations for the Effect of 12 Hours on Transfer

Maximum likelihood estimates

	2000		2001		2002		2003	
	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched
Intercept	-1.19	-1.08	-1.12	-0.84	-1.11	-1.01	-1.12	-0.98
	(.03)	(.05)	(.04)	(.05)	(.03)	(.05)	(.03)	(.04)
12 Hours	0.92	0.79	0.83	0.51	0.81	0.66	0.85	0.67
	(.04)	(.07)	(.04)	(.07)	(.04)	(.05)	(.04)	(.06)
Log Likelihood	-10983.83	-2567.74	-9570.56	-2163.38	-10561.46	-2334.47	-11442.27	-3321.81
Chi2	593.66	139.90	445.22	49.47	475.01	89.33	561.84	129.95
N	15,328	4,110	13,395	3,352	14,391	3,708	16,160	5,238

CALCULATIONS:

Base Probability	23.3%	25.4%	24.6%	30.1%	24.7%	26.8%	24.5%	27.4%
	=exp(intercept) / (1+ exp(intercept))							
Effect of 12+ Credits	43.3%	42.8%	42.9%	41.7%	42.5%	41.4%	43.1%	42.3%
	=exp(intercept + 12hours) / (1+ exp(intercept + 12hours))							
Difference	20.0%	17.4%	18.3%	11.6%	17.8%	14.7%	18.6%	15.0%
	=(Effect of 12hours) - (Base Probability)							
CI Prob Low	41.4%	39.6%	40.9%	38.3%	40.7%	39.0%	41.3%	39.5%
CI Prob High	45.2%	46.1%	44.8%	45.2%	44.4%	43.9%	44.9%	45.2%
	=exp(intercept + (12hours +/- 1.96*SE)) / (1+ exp(intercept + (12hours +/- 1.96*SE)))							
CI Low	18.1%	14.2%	16.3%	8.2%	15.9%	12.2%	16.8%	12.2%
CI High	21.9%	20.7%	20.2%	15.1%	19.6%	17.2%	20.4%	17.8%
	`=(CI Low/High) - (Base Probability							

CHAPTER III

DO COMMUNITY COLLEGES INHIBIT BACCALAUREATE DEGREE ATTAINMENT? A COMPARISON WITH THEIR FOUR-YEAR PEERS

Introduction

A great debate exists today over the role of the community college as a democratizing agent that expands student enrollment or a diversion tool that prevents students from attaining an undergraduate degree (e.g. Leigh & Gill, 2003; Rouse, 1995). From their inception, community colleges are said to have expanded higher education to provide postsecondary training for many—to democratize education—and prepare a pathway to undergraduate degree attainment for disadvantaged students (Cohen & Brawer, 2008). Critics of the community college system claim that such expansion in the two-year sector has further stratified American society by diverting disadvantaged students away from a four-year institution where they would have likely earned an undergraduate degree (Brint & Karabel, 1989; Labaree, 1997).

Current estimates indicate that nearly fifty percent of students make use of the community college as their initial enrolment in higher education. This statistic is in contrast to the roughly thirty-seven percent of students doing the same in the early 1970s (Adelman, 2005; Bailey, Jenkins & Leinbach, 2005). Furthermore, Wirt et al. (2000) show that economically disadvantaged, traditionally underrepresented, and first-generation students are more likely to begin at a community college as opposed to a four-year college or university. Although the overall number of students entering higher education each fall has increased, suggesting an increase in access, research has demonstrated that significant gaps have formed in terms of student persistence and degree attainment, particularly for minority and low-income students. These students have the lowest overall college completion rates (Cabrera, Burkum & La Nasa, 2005; Carey, 2004; Choy, 2000) and the lowest transfer rates (Melguizo & Dowd, 2006; Dougherty & Kienzl, 2006; Lee & Frank, 1990). With expansion into the two-year sector, and particularly with an increasing number of minority and low-income students enrolling in a community college (though not completing a bachelor's degree) a debate is raging over whether community colleges democratize education by expanding enrollment and increasing access or divert students away from a four-year institution where they would have otherwise attained a bachelor's degree (Alfonso, 2006; Cohen & Brawer, 1982; Dougherty, 1987; Gonzalez & Hilmer, 2006; Karabel, 1972; Leigh & Gill, 2003, Medsker, 1960; Melguizo & Dowd, 2009, Rouse, 1995). I contribute to this ongoing debate by examining degree outcomes for commuting college students and their four-year peers using two different statistical approaches, asking, "What is the effect of initial enrollment in a community college on eventual degree attainment as compared to students who began in the four-year sector?"

Background and Context

Previous Studies

Previous studies of degree attainment for community college students have yielded mixed results; however, more contemporary studies suggest that community colleges may be serving to democratize education and expand enrollment without diverting capable, though low-income, students away from a bachelor's degree. By implementing new measures to remove sources of bias, studies have shown that the diversion effect may be much smaller than has been previously stated (Gonzalez & Hilmer, 2006; Leigh & Gill, 2003; Melguizo & Dowd, 2009; Rouse, 1995). I contribute to this conversation by implementing similar methods to account for bias as well as push further to investigate whether the methods implemented were successful in teasing out the extent to which the results remain biased due sample selection.

A Focus on Economic Status

Although a prime directive of the community college is to serve economically disadvantaged students, only in recent years have studies emerged focusing explicitly on the educational outcomes of poor students as compared to their more affluent peers in the community college. A handful of these studies focus on an important step in the degree attainment process for community college students: successful transfer to a four-year institution. Such studies find that transfer rates are generally low for disadvantaged students, with transfer rates falling over twenty-five percent below transfer rates for more affluent peers (Cabrera, Burkum, & LaNasa, in press; Lee & Frank, 1990; Dougherty & Kienzl, 2006). Notably, Dougherty and Kienzl (2006) find that students in the top ten percent of the SES distribution transfer from a community college to a four-year institution at a rate 55% higher than those students in the lowest 10%. Using bachelor's degree attainment as their outcome, Cabrera, Burkum and La Nasa (2005) find that attending a four-year college as opposed to a community college yields upwards of a sixty-nine percent increase of completing an undergraduate degree within ten years. With this seemingly sizeable gap in achievement for low-income students, I seek to better understand this relationship between low-income students beginning at the community college and rising juniors by including a proxy for economic status—free and reduced lunch designation—as an important covariate.

A Focus on Race

A growing body of literature has begun to explore the relationship between race and college completion. Hispanic students, in particular, have begun to enroll in greater numbers in higher education and this is particularly true in Texas (THECB, 2010). Research has demonstrated, however, that a gap of twenty percentage points exists in college completion rates between Hispanic and White students (Melguizo, 2003). Furthermore, Carey (2004) found a similar gap with completion rates of forty-seven percent and forty-six percent for Hispanic and Black students, respectively, compared to sixty-seven percent for White students. Finally, and perhaps most alarming, although Hispanic students doubled their college completion rates during the period 1970 to 1990, no further progress has been made (Vernez & Mizell, 2001). To further explore the relationship between race and college completion for community college transfer students as compared to rising juniors, I will focus heavily on outcomes of Hispanic and Black students.

Additional Factors

In addition to individual characteristics such as economic status and race, other studies have explored the relationship of additional covariates on degree attainment. In a descriptive study using nationally representative data from the National Center for Education Statistics, Bradburn and Hurst (2001) find that transfer rates (an important step in eventual degree completion) are significantly higher for those students who (1) initially enroll in an academic degree program, (2) intend to complete an undergraduate degree, and (3) remain continuously enrolled during the first two years of their postsecondary education.

Multivariate analyses of community colleges and degree attainment point to differences between pre-college academic preparation in the form of the completion of an Advanced Placement (AP) course (Klopfenstein & Thomas, 2005) or International Baccalaureate (IB) course (Bailey & Karp, 2003), the completion of a trigonometry course (Adelman, 1999; Checkley, 2001; Tierney, Colyar, & Corwin, 2003; Long, Iatarola, & Conger, 2009), and performance on the state-wide math exam (Bound, Lovenheim, & Turner, 2009). In addition, previous studies indicate the importance of such community factors as urbanicity, high school enrollment, per-pupil expenditures, pupil-teacher ratio, and the percent minority (Fletcher &

Tienda). Postsecondary factors, too, have been shown to influence degree attainment; these include selectivity (Barron, 1999), the percentage of students in developmental coursework (Bettinger & Long, 2010), the percentage of tenured faculty members (Eagen & Jaeger, 2009), and the overall postsecondary enrollment (Bowen et al., 2008). Additionally, Bound et al. (2007) find that increased hours of employment among college students arises due to a need to meet soaring tuition costs and has a pronounced affect on the amount of time for such students to complete an undergraduate degree.

A Model of Degree Completion

In order to better understand how these factors work together, I appeal to a model of degree attainment for community college students based on a human capital model (Becker, 1967; Mincer, 1974). A basic human capital model would focus largely on skills and abilities acquired by the individual before enrolling and the relative impact of this capital on eventual degree attainment. This model, however, has since been expanded by a number of economists studying college completion in order to include institutional factors that may very well influence the degree attainment patterns of students (e.g. Bowen & Bok, 1998; Dale & Krueger, 2002; Gonzalez & Hilmer, 2006; Kane, 1998; Melguizo, 2003; Rouse, 1995; Melguizo & Dowd, 2009). Additionally, although geared largely to college choice as opposed strictly to completion, Perna (2006) points to the importance of school and community context in her conceptual model of student college choice. In a series of working papers, Flores and Park (in progress) combine these ideas of personal characteristics, skill attainment, high school context, higher education context, economic status, and regional context characteristics into a more complete model in studying higher education access and completion (Flores & Park, in progress; Flores, Ochoa, & Park, in progress). In a similar style of Flores and Park, I group the factors influencing college completion into five groups: student characteristics (S), high school preparation (HS), community context (C), postsecondary characteristics (PS), and an indicator for those students simultaneously working outside of the university in the first semester of the analysis (W). A visual representation of this is presented in Figure 3.

With this college completion model in mind, I determine whether differences exist in the completion rates of community college transfers and rising juniors by conducting probit regression maximum likelihood estimation with the outcome of degree completion (BA), controls for the factors indicated above, (S, HS, C, PS, and W), as well as an indicator (T) for whether a student is a community college transfer student. In the following section, I establish the statistical model and then discuss a potential source of bias—self-selection bias—and two different methods I have employed in order to contend with this bias, so as to produce unbiased estimates of the effect of beginning at a community college and then transferring to a four-year institution on eventual degree attainment.

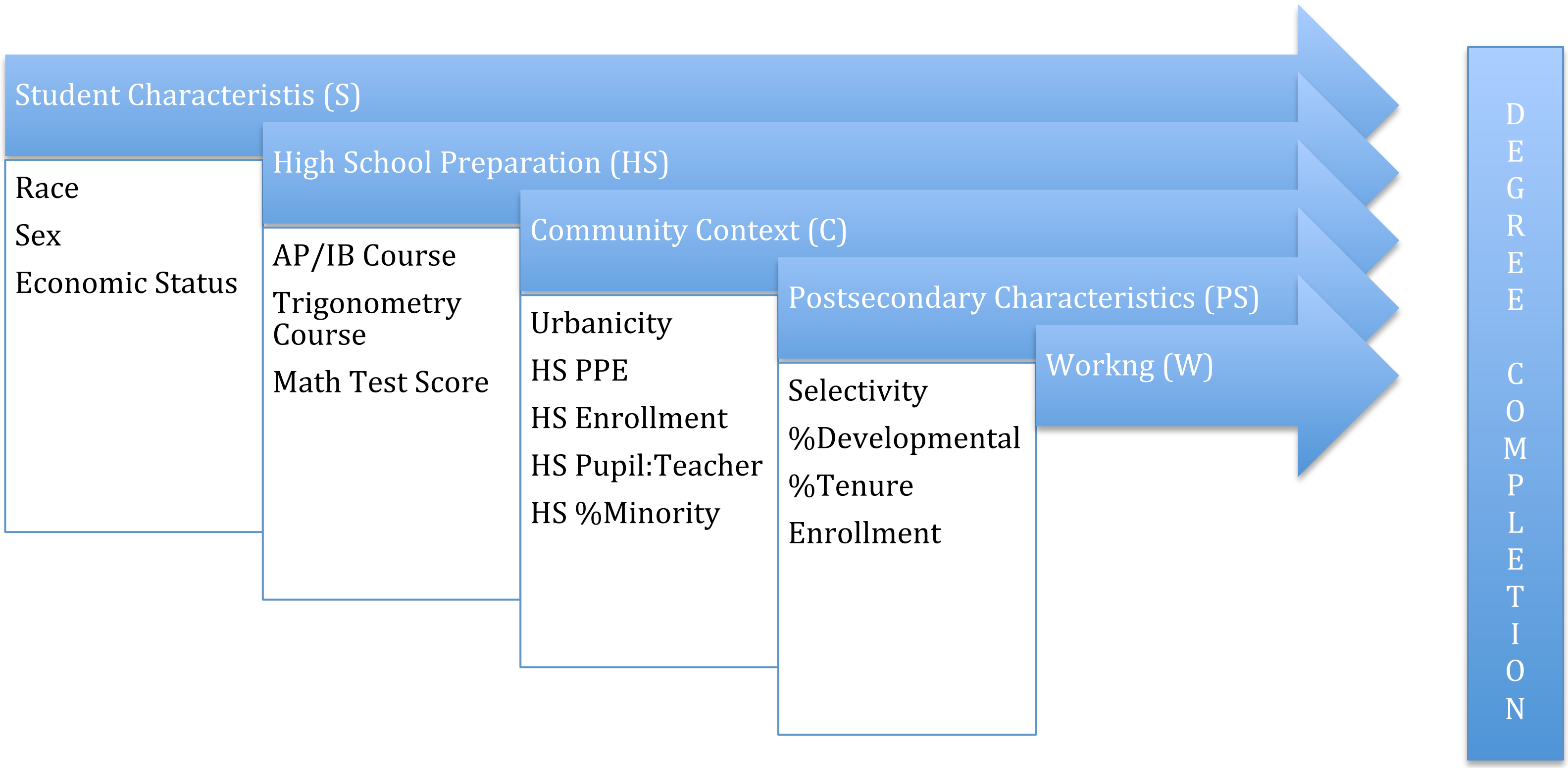

Figure 3: A Conceptual Model of Degree Completion

Unique Contributions

I compare the educational outcomes of those students who began at a community college and successfully transferred to a four-year college or university with a comparative group of students who initially began at a four-year institution and have successfully completed two years of study—termed “rising juniors”. In addition, I explore the effect of minority status on the differences in degree attainment between community college transfer students and rising juniors. I use a relatively underutilized, yet vast, dataset – the Texas Schools Microdata Panel (TSMP) – in order to build a cohort of transfer and rising junior students. This dataset provides student-level data for all public secondary, and all postsecondary institutions in the state, allowing for a relatively complete picture of student postsecondary activity. I contribute in a unique way to the existing literature due, in large part, to the ability to control for a wide variety of student and institutional characteristics.

In addition, I contribute to the democratization/diversion debate by focusing on those students who began at a community college *and* successfully transferred to a four-year college or university in comparison to their peers who began at a four-year school. This approach allows for a clearer testing of the democratization/diversion effect by disentangling the idea of intent. I include only those community college students who successfully transfer to a four-year institution. Although many students beginning at a community college may have the espoused intent of bachelor’s degree attainment, I argue that these students—the transfers—have the clear intent to obtain a bachelor's degree as they have successfully completed a major step in the degree attainment process. As it is highly likely that the rising juniors also intend to complete a bachelor's degree, any difference in the educational outcomes between the two groups, after controlling for observed student and institutional characteristics, would speak to the democratization/diversion debate. After completing the analysis, a statistically significant gap in the achievement of these two groups would suggest a diversion effect.

In order to better inform the field on the differences in college completion rates for community college transfer students and four-year rising juniors, I specifically ask: "What is the effect of initial enrollment in a community college on eventual degree attainment for students graduating from high school, immediately enrolling in the community college and successfully transferring to a four-year college or university as compared to students who began in the four-year sector?" What follows is research design, including a statistical approach, followed by a results section and a general discussion before offering concluding comments.

Research Design

Basic Statistical Approach

A basic probit model using maximum likelihood estimation accounting for transfer status is specified as follows:

$$\Phi^{-1}(p_i) = \beta_0 + \beta_T T_i$$

where Φ^{-1} is the inverse cumulative distribution function of the standard normal and p_i = Pr(y_i = 1) denotes the probability that student *i* successfully completes a baccalaureate degree. Similarly, a model incorporating the factors identified in Figure 3 is specified as:

$$\Phi^{-1}(p_i) = \beta_0 + \beta_T T_i + \beta_s S_i + \beta_{HS} HS_i + \beta_C C_i + \beta_{PS} PS_i + \beta_W W_i$$

While the model accounts for all of the factors in the degree attainment model, I am primarily interested in the estimate for β_T, the impact of being a community college transfer student on degree attainment.

Self-Selection Bias

Inherent in the estimation of the transfer effect is the issue of self-selection. In this instance, we are worried that certain unobservable characteristics of the individuals cause the students to “self-select” into a particular type of institution. If, for instance, more motivated students are inclined to begin at a four-year institution and the same highly motivated students are also more likely to obtain an undergraduate degree, any estimate of a transfer effect would be biased away from zero and would reflect a greater differential between community college transfer students and rising juniors. A series of earlier studies on the effect of community college transfer have failed to account for this effect (e.g. Anderson, 1981; Cabrera, Burkum, & La Nasa (in press); Ganderton & Santos, 1995; Lee, Mackie-Lewis, & Marks, 1993; Nunley & Breneman, 1988; Velez, 1985). More recent studies, however, have accounted for this potential bias and have demonstrated less of a diversion effect (Alon, 2005; DesJardins, Ahlburg, & McCall, 2006; Melguizo & Dowd, 2009; Titus, 2007). Long and Kurlaender (2009) utilize two different methods for correcting for bias—instrumental variables and propensity score matching. Similarly to their work, though with a vastly different data set and context, I implement these strategies.

Instrumental Variables Procedure

A widely regarded method for correcting for this potential bias is the use of a two-stage instrumental variables procedure (Heckman, 1979; Lee, 1983). Thus, my final probit model includes a two-stage correction procedure to remove potential bias. This procedure involves estimating the propensity of beginning at a community college by using one or more instruments and then entering the predicted value into the structural equation. I define three instruments as the average tuition at a public four-year institution in a student's region of the state, the minimum distance to a two-year institution, and a lagged measure of county unemployment.[9] Long and Kurlaender (2008), Melguizo (2003), as well as Melguizo and Dowd (2009) implement similar instruments. For the first instrument, I divide

[9] The lagged unemployment rate represents the unemployment rate at the time the student graduated from high school.

the state into economic regions as defined by the Office of the Comptroller. I then calculate the average tuition for a public four-year college or university within each region. For the second, I calculate the distance between a student's high school and all institutions of higher education within the state; I then select the minimum distance as the instrument. For the third instrument, I use the county unemployment rate at the time of high school graduation.

This procedure is implemented using Heckman's (1979) two-stage bias correction method as follows: First, I estimate the propensity to be a community college transfer student (T) as:

$$T_i = \gamma Z_i$$

In this equation, Z is a vector of all of the pre-college characteristics (S, HS, & C) from above well as the three instruments. This gives the predicted value $\widehat{T_i} = \hat{\gamma} Z_i + u_i$ that is then substituted into the structural equation, yielding:

$$\Phi^{-1}(p_i) = \beta_0 + \beta_T \hat{T}_i + \beta_s S_i + \beta_{HS} HS_i + \beta_C C_i + \beta_{PS} PS_i + \beta_W W_i$$

In using this procedure, it is warranted to engage in the benefits but also the limitations of such instruments. In this line of inquiry, it is difficult to find a good instrument that satisfies both assumptions of instrumental variables as established by Heckman (1979). First, the instrument must be uncorrelated with u, Cov(z,u) = 0, and it must be correlated with the endogenous variable, in this case: transfer, such that Cov(z,t) ≠ 0. In order to satisfy the first condition, I argue that regional tuition is unrelated to motivation. In a national sample, Melguizo and Dowd (2009) find that state average tuition satisfies this requirement. Though at a sub-state level, I argue that the same will hold true for regionality within Texas due to a similar rationale: I expect to find a random distribution of motivated students across the state as home location is determined by parental choice and not student motivation. With regard to the second instrument, I argue that proximity to postsecondary education will be unrelated to a student's eventual educational outcome. With regard to the third instrument, it seems unlikely that a lagged county unemployment rate will be linked to graduation six years later.

In order to satisfy the second condition, average regional tuition, proximity, and local unemployment rates must be unconditionally correlated with being a transfer student. This correlation is anticipated as previous research has demonstrated that students are responsive to the tuition and relative abundance of lower cost postsecondary options within a geographic region (Kienzel, Alfonso, & Melguizo, 2007). In other words, students may be more likely to be a transfer student based on the relative tuition and proximity of nearby four-year institutions—the more costly the four-year tuition, the more likely a student may be to enroll in a community college and appear in the dataset as a transfer student. Also, students may be more inclined to enroll in a community based on the economic conditions at the time of enrollment, yet six years later it seems unlikely that these original unemployment rates will affect degree outcomes, satisfying the first condition. To empirically investigate whether both of these conditions hold, I present results from the first stage regression, include an F-test, and tests for the identification of the instruments (Wooldridge, 1999). I turn now to a matching procedure also used to remove bias from the estimates.

Matching Procedure

Empirically, the variable y_1 represents the postsecondary graduation outcome for students who did begin at the community college and y_0 represents the outcome for those who did not. The impact of beginning a community college is then given by the difference in these two outcomes (Smith & Todd, 2001):

$$\Delta = y_1 - y_0$$

In this paper, however, I seek to reach a unbiased estimate and thus, as one approach, turn to matching techniques. In doing so, I seek an estimate for the Average Treatment on the Treated (ATT) where the specified treatment is considered beginning at a community college. The ATT estimates the mean effect of the treatment on those receiving it with respect to what the outcome would have been for the same students had they not received it, expressed as

$$ATT = E(\Delta \mid x, z{=}1) = E(y_1 - y_0 \mid x, z{=}1) =$$

$$E(y_1 \mid x, z{=}1) - E(y_0 \mid x, z{=}1)$$

where $z = 1$ represents those students who begin at a community college and $z = 0$ represents "rising juniors" and $\boldsymbol{x}$ is a vector of characteristics that may explain college outcomes in addition to whether a student started at a community college.

Data exist for outcomes amongst the treated ($E(y_1 \mid x, z{=}1)$); what is not known, however, is information about the counterfactual [the outcome of those same students had they not received treatment: $E(y_0 \mid x, z{=}1)$]. Ideally, a counterfactual would be established using a control group in an experimental design selected at random with respect to the other characteristics $\boldsymbol{x}$ (Heckman, 1979). In instances such as this when experimental design is not feasible, however, one option is to turn to matching techniques (Rubin, 1974, 1976).

Essentially, I match students beginning in the two- and four-year sectors on a number of covariates to tease out the true impact of beginning at a community college. Empirically, I establish α, the matching estimator, by comparing the outcomes for the treatment group with the comparison group conditional upon a propensity for being a member of the treatment group, p (Smith & Todd, 2001):

$$\text{Let } \alpha = E(y_1 - y_0 \mid z{=}1) =$$

$$E(y_1 \mid z{=}1) - E_{p|z=1}\, E_y\, (y \mid z{=}1, p) =$$

$$E(y_1 \mid z{=}1) - E_{p|z=1} E_y (y \mid z{=}0, p)$$

Then, I define the propensity to receive treatment p as $\Pr(z{=}1 \mid x) < 1$ for all x, and I define the matching estimator as: $\alpha_M = \frac{1}{n_1} \sum_{i \in I_i \cap s_p} [\, y_{1i} - \hat{\mathrm{E}}(y_{0i} \mid z = 1,\ p_i)]$, where $\hat{\mathrm{E}}(y_{0i} \mid z = 1, p_i)$ represents the matched outcome, S_p is the region of common support between the two groups, and n_1 is the number of individuals in in the set $I_1 \cap S_p$. I then complete a final logistic regression analysis using only students who are similar along the specified characteristics, except in which sector they began their studies, and thus have similar propensities p to enroll in a community college. Using this procedure, I am able to obtain an estimate for the ATT. To confirm the balance of the samples (the extent to which the treatment and comparison groups are similar excepting only for initial sector enrollment) I conduct t-tests between the vector $\boldsymbol{x}$ and whether or not a student began in a community college—a successful match will yield no statistically significant results in the matched sample.

Data

The data for this study come from a relatively underutilized, though rich, confidential, dataset: the Texas Schools Microdata Panel (TSMP). The TSMP is a restricted use administrative dataset that includes information on secondary school records and postsecondary education outcomes from 1992 through 2010. In addition, I access individual wage information from the Texas Workforce Commission by utilizing a dataset containing income data on each Texas resident over the same timeframe. Finally, I incorporate data from the United States Department of Education's Common Core of Data (CCD) and Integrated Postsecondary Education Data System (IPEDS). The combination of these datasets provides a wealth of information only recently used for education research.

The dependent variable is successful completion of a bachelor's degree. From the first year of study (the third year of study for the rising juniors), I allow four years of additional time to complete a baccalaureate degree. Conventional graduate rates are often calculated at a total of six years, which is 150% of the intended degree program length. This specification results in an overall completion period of six years. This variable is constructed by the author using several years of TSMP data.

The independent variable of interest is the indicator (T) of whether a student began at a community college and transferred instead of a student beginning at a four-year institution. Other variables include: student characteristics (S): race, sex, economic status, and LEP status; high school preparation characteristics (HS):

AP/IB coursework, a trigonometry course, dual enrollment, and math test score; community context characteristics (C): unemployment, urbanicity, high school per pupil expenditures, high school enrollment, high school percent minority, high school pupil-teacher ratio, and high school percent minority; postsecondary characteristics (PS): institutional selectivity, percent developmental, percent tenured faculty, student-faculty ratio, and full-time equivalent enrollment; and an indictor for whether a student worked (W) during the first year at the four-year institution for the community college beginners and the third year at the four-year school for rising juniors.

Data on race, sex, economic status, LEP status, AP/IB coursework, trigonometry coursework, dual enrollment, math test score are available from the TSMP. Data on unemployment and wage data are available from the Texas Comptroller. All remaining community context variables are available from the CCD. Postsecondary selectivity is based on the Barron index, data on the percent in developmental courses, and the percent tenured come from the TSMP. All remaining postsecondary variables come from IPEDS.

To conduct this analysis I construct a cohort of students comprised of students who began in a community college in the fall of 2002 and successfully transferred to a four-year institution by the fall of 2004. I then compare the outcomes of these students who began at a four-year institution and have earned sixty credits by the fall of 2004. Outcomes for all of the students are followed through 2008, allowing for an undergraduate degree completion time of six years. Descriptive statistics are provided in Table 8. Based solely on descriptive statistics, we see a six-year degree completion rate differential of 8.6%, 9.1%, 10.9%, and 21.3% for All, White, Hispanic, and Black students respectively. In the next section, I present results from the analyses aimed at removing selection bias into a community college and present a less biased estimate of the completion rate differential.

Table 8

Descriptive Statistics for Community College Transfers and Four-Year Peers

	Full Sample				White				Hispanic				Black			
	CC Transfers		Four-Year Peers		CC Transfers		Four-Year Peers		CC Transfers		Four-Year Peers		CC Transfers		Four-Year Peers	
	n=5,440		n=26,112		n=3,714		n=15,926		n=1,025		n=4,805		n=412		n=2,962	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Six-Year Degree Complete	0.667	0.471	0.763	0.425	0.701	0.458	0.792	0.406	0.607	0.489	0.716	0.451	0.415	0.493	0.628	0.483
Student Characteristics (S)																
Hispanic	0.188	0.391	0.184	0.388												
Black	0.076	0.265	0.113	0.317												
Asian	0.033	0.178	0.076	0.266												
Male	0.466	0.499	0.430	0.495	0.477	0.500	0.435	0.496	0.434	0.496	0.435	0.496	0.408	0.492	0.357	0.479
Economic Disadvantage	0.141	0.348	0.145	0.352	0.033	0.178	0.028	0.164	0.454	0.498	0.460	0.498	0.299	0.458	0.285	0.452
High School Preparation (HS)																
AP/IB Course	0.427	0.495	0.708	0.455	0.423	0.494	0.727	0.446	0.487	0.500	0.705	0.456	0.260	0.439	0.478	0.500
Trig Course	0.510	0.500	0.726	0.446	0.520	0.500	0.753	0.432	0.522	0.500	0.682	0.466	0.323	0.468	0.549	0.498
Math Exam Score	51.876	8.683	53.899	8.847	52.472	8.514	54.431	8.960	51.743	7.797	53.591	7.837	47.124	9.325	50.363	9.127
Community Context (C)																
Pupil-Teacher Ratio	14.598	2.487	15.155	2.250	14.368	2.440	14.978	2.325	15.001	2.728	15.089	2.274	14.826	2.259	15.364	2.019
HS Percent Minority	0.407	0.275	0.441	0.285	0.306	0.194	0.322	0.203	0.724	0.276	0.734	0.266	0.553	0.262	0.653	0.269
HS PPE/1000	4.315	0.531	4.294	0.526	4.316	0.562	4.282	0.559	4.359	0.514	4.377	0.540	4.258	0.367	4.276	0.434
Urbanicity	0.349	0.477	0.431	0.495	0.259	0.438	0.333	0.471	0.552	0.498	0.560	0.496	0.519	0.500	0.618	0.486
Worked (W)																
Working Indicator	0.142	0.349	0.123	0.329	0.144	0.351	0.124	0.329	0.122	0.327	0.115	0.319	0.155	0.363	0.161	0.368
Postsecondary Characteristics (PS)																
Barron (dummy for low)	0.638	0.481	0.468	0.499	0.654	0.476	0.435	0.496	0.449	0.498	0.401	0.490	0.838	0.369	0.838	0.369
PS Percent Developmental	0.054	0.112	0.057	0.130	0.039	0.039	0.035	0.039	0.049	0.068	0.056	0.074	0.200	0.323	0.200	0.323
PS Percent Tenure	0.450	0.072	0.471	0.077	0.446	0.067	0.469	0.072	0.472	0.080	0.477	0.078	0.472	0.079	0.472	0.079
PS Enrollment/1000	1.906	1.218	2.607	1.550	2.029	1.276	2.803	1.520	1.600	1.032	2.143	1.462	1.608	1.211	1.608	1.211

Results

For brevity, estimates for the effect of transferring from a community college (β_T) are provided in Table 9, by race. Full results for all of the covariates are provided in the appendix and predicted probabilities for each model are provided in Table 10; however, as the IV Probit model did not produce statistically significant differences, I do not include any predicted probabilities from it in Table 10. I provide estimates from the first stage analysis in the appendix.

Table 9

CC Transfer Results as Compared to 4yr Peers, Comparing Models

	1	2	3			4
	Basic Model	Full Probit Model	IV Probit Model			Matched Model
			Estimate	Wald Test chi2	Wald Prob > chi2	
All Students						
Estimate	-0.2775***	-0.1733***	-0.1657	0.85	0.3553	-0.1766***
[SE]	[0.02]	[0.02]	[0.38]			[0.04]
chi2	204.1551	1999.8001	1823.5073			24.8798
White						
Estimate	-0.2834***	-0.1543***	-0.399	0.29	0.5921	-0.1750***
[SE]	[0.02]	[0.03]	[0.37]			[0.03]
chi2	136.292	757.2245	699.5136			31.2318
Hispanic						
estimate	-0.2881***	-0.2078***	1.0873	0.75	0.3872	-0.1396*
[SE]	[0.04]	[0.05]	[1.23]			[0.06]
chi2	43.2925	331.35	263.5167			5.9911
Black						
Estimate	-0.5125***	-0.4628***	0.3178	1.53	0.2164	-0.3821***
[SE]	[0.07]	[0.07]	[1.23]			[0.09]
chi2	62.5989	482.6252	393.6203			18.252

** p<0.05, ** p<0.01, *** p<0.001*

Table 10:
Predicted Probabilities of BS/BA Attainment for CC Transfers and 4yr Peers Comparing Models and Outcomes by Race

	1	2	3	4
		Full Probit	IV Probit	Matched
	Basic Model	Model	Model	Model
All				
CC Transfer	67.04%	71.11%	n/a	67.45%
4yr Peer	76.38%	76.73%	n/a	73.53%
Difference:	-9.34%	-5.62%	n/a	-6.08%
White				
CC Transfer	70.29%	74.50%	n/a	70.11%
4yr Peer	79.28%	79.19%	n/a	75.88%
Difference:	-8.99%	-4.69%	n/a	-5.77%
Hispanic				
CC Transfer	61.65%	64.85%	n/a	60.52%
4yr Peer	71.65%	71.85%	n/a	65.77%
Difference:	-10.00%	-7.00%	n/a	-5.25%
Black				
CC Transfer	42.69%	45.01%	n/a	42.05%
4yr Peer	62.87%	63.21%	n/a	63.12%
Difference:	-20.18%	-18.20%	n/a	-21.07%

Differences are not reported for coefficeints that are not statistically significant

Column 1 is the basic model containing only an indicator for transfer status and no other covariates; column 2 is the model without instruments (but with all of the covariates); column 3 is the model using instruments; and column 4 is the model using propensity score matching. The basic model (1) shows a strong negative impact for those students beginning in the community college sector as reflected in the descriptive statistics. The full model also shows a strong negative impact between beginning a community college and degree attainment. Just as found by Melguizo and Dowd (2009), however, the effect of transferring from a community college appears to vanish after instrumentation as compared to their four-year peers (column 3). These results are highly questionable, however, given the Wald statistic used in the test of weak identification where p = 0.3553 in the full sample.[10] In other words, this model has not satisfied the assumption that the instruments are uncorrelated with the final outcome—a scenario that has received attention by many as a critique of conducting an analysis using tuition and proximity as instruments.[11] Given the results of this test, these results should be viewed with extreme caution. Results from the first stage of each of the instrumental variable analyses are provided in the appendix.

Results from the matching analysis are provided in column 4. In all of the analyses, the point estimate remains negative and statistically significant. While in the full and White samples, the effect of beginning at a community college on the likelihood of six-year degree attainment becomes weaker (from 9.4% to 6.8% in the full sample and from 9.1% to 5.4% in White sample), the same is not true for the Hispanic and Black samples. In the matched sample, Hispanic and Black students have a higher baseline likelihood of completion; however, the effect of being a community college transfer student decreases six-year degree completion by 14.9% for Hispanic students and 35.9% for Black students. Given the t-tests of group equivalence (see Table 11) where the samples balance in all but one area, these results suggest a strong negative effect when comparing similar students who differ only by where they began their pursuit of higher education.

[10] Specifically, I use the Kleibergen-Paap Wald statistic where the null hypothesis is a weak identification of the instruments.
[11] Long and Kurlaender (2009) make use of similar instruments and find similar results regarding the test of exogeneity.

Table 11:
T-tests results for the Unmatched and Matched Samples, CC Transfers and 4yr Peers

	All		White		Hispanic		Black	
	UnMatched	Matched	UnMatched	Matched	UnMatched	Matched	UnMatched	Matched
Hispanic	-4.607	1.135						
Black	-10.072	0.503						
Asian	-9.195	1.102						
Male	2.399	0.317	2.388	1.059	-0.968	1.314	1.016	1.369
Economic Disadvantage	-29.582	-0.747	-28.610	-0.193	-7.687	0.113	-5.623	-0.760
AP/IB Course	-20.982	0.000	-20.846	0.327	-4.947	-0.108	-5.566	-1.723
Trig Course	-9.939	-0.647	-9.807	-0.221	-2.289	-0.677	-4.599	-1.122
Math Exam Score	-6.062	0.968	-0.887	0.843	-1.904	-0.633	-0.499	0.411
Pupil-Teacher Ratio	-14.174	-0.794	-12.044	-0.758	-0.314	-0.312	-5.404	-0.068
HS Percent Minority	-13.652	-0.115	-5.983	0.648	-3.123	0.457	-8.323	1.179
HS PPE/1000	1.198	0.664	1.930	0.368	-1.044	-0.702	-0.552	1.375
Urbanicity	-11.841	0.755	-8.059	-1.230	-0.652	0.738	-4.273	0.612
Wages	1.725	0.777	0.889	1.201	0.234	-0.331	-0.320	0.740
Barron (dummy for low)	16.161	1.116	16.830	-0.792	2.188	-0.434	4.135	-2.282
PS Percent Developmental	-5.055	0.035	4.563	-0.130	-4.389	-1.366	-1.473	0.626
PS Percent Tenure	-15.814	0.875	-14.405	0.181	-1.452	-1.088	-4.648	1.702
PS Enrollment/1000	-20.275	0.954	-20.012	0.789	-6.431	1.264	-2.232	-0.906

Discussion

These results both corroborate as well as call into question previous findings and demonstrate that the effects of community college transfer are not uniform across race. As compared to other students within their race, White students transferring from the community college experience less of a "transfer effect" than Hispanic and Black students. After matching on the set of covariates in this study, minority students who begin at the community college are substantially less likely to complete a baccalaureate degree than those minority students who began in the four-year sector. A completion differential of 14.9% for Hispanic students and a sizeable 35.9% differential for Black students demonstrate that the community college may not be adequately serving minority populations. Conversely, there may be factors in play at a four-year institution that, devoid of these first two years there, community college students may suffer. Put differently, instead of community colleges ill-preparing minority students for success, four-year schools may be instilling support mechanisms for minority students that increase graduation rates for those students who initially enroll there. Further research is warranted on the experience of Hispanic and Black student during their first two years at either a community college or a four-year institution. I have only unearthed the differential achievement—future work must ask questions of *why* this differential exists.

Methodologically, given the findings regarding the tests of exogeneity of instruments in the iv probit model, future studies making use of instrumental variables such as proximity and tuition are advised to use caution and test for the validity of such instruments. Additionally, given the differences observed by race, future studies examining the college completion story are advised to examine differential outcomes by race. While it seems likely that the debate over the role of the community college will continue, this paper has challenged the democratization argument: community college transfer students are less likely to complete a bachelor's degree than their four-year peers, though the effect fades for White students but increases for Black and Hispanic students.

Conclusions

To many, including those at an October 2010 White House summit (The White House, 2010), the American community college is seen as a great equalizer that will serve to provide disadvantaged students with the opportunity to enroll in higher education. The reality, however, is that while enrollment may increase, overall student success, in terms of degree completion, is not the same for those students beginning at a community college. In the absence of policies directed at not only expanding enrollment but *also* increasing student success, we will continue to see differential outcomes for students beginning in the two-year sector. While the effect for White students decreases after conditioning on pre-college characteristics, the completion differential for Hispanic and Black students remains sizeable. Whether an extraordinarily strong experience during the first two years at a four-year institution or a negative experience/preparation during the first two years at a community college, these two groups are not performing equally—particularly for minority students. The success story for minority students beginning in a community college as compared to their four-year peers is not the same.

Do community colleges inhibit baccalaureate degree attainment as compared to their four-year peers? It appears as though they do; at least for now, and particularly for minority students.

Appendix

Table 12a

Full Results of CC Transfer and 4yr Peers, All Students

	Basic Model	Full Probit Model	IV Probit Model	Matched Model
CC Transfer	-0.2775***	-0.1733***	-0.1657	-0.1766***
	[0.02]	[0.02]	[0.38]	[0.04]
Student Characteristics				
Hispanic		-0.1110***	-0.0957***	
		[0.03]	[0.03]	
Black		-0.1618***	-0.1663**	
		[0.03]	[0.05]	
Asian		-0.0888**	-0.0874*	
		[0.03]	[0.04]	
Male		-0.1592***	-0.1582***	
		[0.02]	[0.02]	
Economic Disadvantage		-0.1649***	-0.1560***	
		[0.03]	[0.03]	
High School Preparation (HS)				
AP/IB Course		0.0758***	0.0775	
		[0.02]	[0.05]	
Trig Course		0.1700***	0.1690***	
		[0.02]	[0.04]	
Math Exam Score		0.0041***	0.0041***	
		[0.00]	[0.00]	
Pupil-Teacher Ratio		0.0063	0.0068	
		[0.00]	[0.01]	
HS Percent Minority		-0.1593***	-0.1293**	
		[0.04]	[0.04]	
HS PPE/1000		0.0003	-0.0047	
		[0.02]	[0.02]	
Urbanicity		-0.0101	-0.0155	
		[0.02]	[0.02]	
Worked (W)				
Working Indicator		0.0042	0.0024	
		[0.02]	[0.02]	
Postsecondary Characteristics (PS)				
Barrom (dummy for low)		-0.1026***	-0.1133***	
		[0.02]	[0.02]	
PS Percent Developmental		-0.7151***	-0.7121***	
		[0.07]	[0.07]	
PS Percent Tenure		0.201	0.1992	
		[0.11]	[0.15]	
PS Enrollment/1000		0.0085***	0.0081***	
		[0.00]	[0.00]	
Constant	0.7186***	0.3271*	0.2112	0.6290***
	[0.01]	[0.16]	[0.31]	[0.03]
N	31552	31552	31552	5592
chi2	204.1551	1999.8001	1823.5073	24.8798
Wald chi2	n/a	n/a	0.85	n/a
Wald Prob > chi2	n/a	n/a	0.3553	n/a

** p<0.05, ** p<0.01, *** p<0.001*

Table 12b

Full Results of CC Transfer and 4yr Peers, White

	Basic Model	Full Probit Model	IV Probit Model	Matched Model
CC Transfer	-0.2834***	-0.1543***	-0.399	-0.1750***
	[0.02]	[0.03]	[0.37]	[0.03]
Student Characteristics				
Male		-0.1190***	-0.1108***	
		[0.02]	[0.02]	
Economic Disadvantage		-0.3302***	-0.3299***	
		[0.06]	[0.06]	
High School Preparation (HS)				
AP/IB Course		0.0129	-0.0239	
		[0.02]	[0.06]	
Trig Course		0.1520***	0.1270**	
		[0.02]	[0.04]	
Math Exam Score		0.0019	0.0014	
		[0.00]	[0.00]	
Pupil-Teacher Ratio		0.0085	0.0066	
		[0.01]	[0.01]	
HS Percent Minority		-0.1305*	-0.1244*	
		[0.06]	[0.06]	
HS PPE/1000		0.0128	0.0116	
		[0.02]	[0.02]	
Urbanicity		-0.0188	-0.0224	
		[0.03]	[0.03]	
Worked (W)				
Working Indicator		-0.0291	-0.0282	
		[0.03]	[0.03]	
Postsecondary Characteristics (PS)				
Barrom (dummy for low)		-0.1350***	-0.1321***	
		[0.03]	[0.03]	
PS Percent Developmental		-0.7714*	-0.7837**	
		[0.30]	[0.30]	
PS Percent Tenure		-0.0572	-0.121	
		[0.16]	[0.19]	
PS Enrollment/1000		0.0000***	0.0000***	
		[0.00]	[0.00]	
Constant	0.8162***	0.3465	0.4677	0.7025***
	[0.01]	[0.23]	[0.33]	[0.02]
N	19640	19640	19640	7380
chi2	136.292	757.2245	699.5136	31.2318
Wald chi2	n/a	n/a	0.29	n/a
Wald Prob > chi2	n/a	n/a	0.5921	n/a

** p<0.05, ** p<0.01, *** p<0.001*

Table 12c

Full Results of CC Transfer and 4yr Peers, Hispanic

	Basic Model	Full Probit Model	IV Probit Model	Matched Model
CC Transfer	-0.2881***	-0.2078***	1.0873	-0.1396*
	[0.04]	[0.05]	[1.23]	[0.06]
Student Characteristics				
Male		-0.2401***	-0.2502***	
		[0.04]	[0.04]	
Economic Disadvantage		-0.1399***	-0.1094*	
		[0.04]	[0.05]	
High School Preparation (HS)				
AP/IB Course		0.1211**	0.2601	
		[0.04]	[0.14]	
Trig Course		0.1959***	0.2678***	
		[0.04]	[0.08]	
Math Exam Score		0.0076***	0.0106**	
		[0.00]	[0.00]	
Pupil-Teacher Ratio		0.0067	0.005	
		[0.01]	[0.01]	
HS Percent Minority		-0.2108*	-0.1459	
		[0.10]	[0.10]	
HS PPE/1000		-0.021	-0.0019	
		[0.04]	[0.05]	
Urbanicity		-0.0294	-0.0413	
		[0.04]	[0.04]	
Worked (W)				
Working Indicator		0.0402	0.0457	
		[0.06]	[0.06]	
Postsecondary Characteristics (PS)				
Barron (dummy for low)		-0.0527	-0.0098	
		[0.05]	[0.07]	
PS Percent Developmental		-0.6415*	-0.0668	
		[0.27]	[0.58]	
PS Percent Tenure		0.8405**	1.0031**	
		[0.27]	[0.35]	
PS Enrollment/1000		0.0000***	0.0000*	
		[0.00]	[0.00]	
Constant	0.5725***	-0.1962	-1.0638	0.4063***
	[0.02]	[0.35]	[0.87]	[0.04]
N	5830	5830	5830	2016
chi2	43.2925	331.35	263.5167	5.9911
Wald chi2	n/a	n/a	0.75	n/a
Wald Prob > chi2	n/a	n/a	0.3872	n/a

** p<0.05, ** p<0.01, *** p<0.001*

Table 12d:
Full Results of CC Transfer and 4yr Peers, Black

	Basic Model	Full Probit Model	IV Probit Model	Matched Model
CC Transfer	-0.5125***	-0.4628***	0.3178	-0.3821***
	[0.07]	[0.07]	[1.23]	[0.09]
Student Characteristics				
Male		-0.3070***	-0.3180***	
		[0.05]	[0.05]	
Economic Disadvantage		-0.1174*	-0.1239*	
		[0.05]	[0.05]	
High School Preparation (HS)				
AP/IB Course		0.2498***	0.2951**	
		[0.05]	[0.09]	
Trig Course		0.1952***	0.2434**	
		[0.05]	[0.09]	
Math Exam Score		0.0093***	0.0109**	
		[0.00]	[0.00]	
Pupil-Teacher Ratio		-0.0231	-0.013	
		[0.01]	[0.02]	
HS Percent Minority		-0.4839***	-0.4142**	
		[0.11]	[0.15]	
HS PPE/1000		-0.0709	-0.0451	
		[0.06]	[0.07]	
Urbanicity		0.1244*	0.1152	
		[0.06]	[0.06]	
Worked (W)				
Working Indicator		0.0442	0.0608	
		[0.06]	[0.07]	
Postsecondary Characteristics (PS)				
Barrom (dummy for low)		0.0442	0.0608	
		[0.06]	[0.07]	
PS Percent Developmental		-0.7387***	-0.7478***	
		[0.08]	[0.08]	
PS Percent Tenure		0.6695*	0.9237	
		[0.32]	[0.51]	
PS Enrollment/1000		0.0000*	0.0000*	
		[0.00]	[0.00]	
Constant	0.3283***	0.2799	-0.8934	0.1911**
	[0.02]	[0.83]	[1.21]	[0.06]
N	3374	3374	3374	792
chi2	62.5989	482.6252	393.6203	18.252
Wald chi2	n/a	n/a	1.53	n/a
Wald Prob > chi2	n/a	n/a	0.2164	n/a

** p<0.05, ** p<0.01, *** p<0.001*

Table 13

First Stage Regression Results Predicting Initial Enrollment in a CC as Compared to a 4yr Institution

	All		White		Hispanic		Black	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Instruments								
Proximity	-0.001	0.000 ***	-0.002	0.000 ***	-0.001	0.000 **	-0.001	0.001
Regional Tuition	0.000	0.000 ***	0.000	0.000 ***	0.000	0.000 ***	0.000	0.001
Lagged Unemployment Rate	0.017	0.002 ***	0.023	0.003 ***	0.010	0.004	0.027	0.008 ***
Student Characteristics (S)								
Hispanic	-0.005	0.007						
Black	-0.119	0.008 ***						
Asian	-0.031	0.008 ***						
Male	0.025	0.004 ***	0.032	0.005 ***	0.009	0.010	0.015	0.011
Economic Disadvantage	-0.005	0.007 ***	-0.004	0.016	-0.022	0.011 ***	0.006	0.012
High School Preparation (HS)								
AP/IB Course	-0.133	0.005 ***	-0.151	0.006 ***	-0.108	0.011 ***	-0.060	0.013 ***
Trig Course	-0.088	0.005 ***	-0.104	0.006 ***	-0.055	0.011 ***	-0.062	0.013 ***
Math Exam Score	-0.002	0.000 ***	-0.002	0.000 ***	-0.002	0.001 ***	-0.002	0.001 ***
Community Context (C)								
Pupil-Teacher Ratio	-0.008	0.001 ***	-0.010	0.002 ***	0.002	0.003	-0.013	0.003 ***
HS Percent Minority	-0.030	0.011 **	-0.014	0.015	-0.017	0.028	-0.099	0.026 ***
HS PPE/1000	-0.008	0.005	0.002	0.006	-0.019	0.011	-0.033	0.014 ***
Urbanicity	-0.014	0.005 **	-0.026	0.007 ***	-0.002	0.013	0.012	0.014
Predictive Power in First Stage								
F-test	544.650		513.336		431.448		484.937	

** p<0.05, ** p<0.01, *** p<0.001*

CHAPTER IV

WORKING HARD FOR THE DEGREE: AN EVENT HISTORY ANALYSIS OF THE IMPACT OF WORKING WHILE SIMULTANEOUSLY ENROLLED

Introduction

The success of college students, and particularly those beginning at the community college, has become a focus for many policymakers. Completion rates paint a sad story, particularly at the community college where less than twenty-five percent of full-time students receive a bachelor's degree within six years (Snyder & Dillow, 2010). These completion statistics have remained relatively unchanged despite the deep investment made by state governments, federal programs, and institutional investments in higher education as a means to reduce the financial burden on students (Singell, 2004). It is, therefore, paramount that we better understand the factors associated with degree completion, particularly for community college students who represent a growing—though vulnerable—segment of American higher education (Wirt et al., 2000).

In this study, I model the factors that, over time, influence baccalaureate degree attainment, with a particular focus on working while simultaneously enrolled. In addition to the ability to track students over a number of years, one of the prime benefits of using a longitudinal student-level dataset is the ability to include individual-level covariates that change over time. I am particularly interested in the role of wages earned while currently enrolled and the influences these wages have on degree attainment. As Cohen and Brawer (2008) report, community college students tend to have higher numbers of working hours and also tend to be less likely to complete as a result of increased demands in the workplace. Working is a large component of the lives of many community college students and, as such, I probe the role of relative wages earned in order to tell a more complete story of the degree completion for community college students. In order to better inform the field of the factors influencing degree attainment for community college students, with a particular focus on wages earned, I ask: "What are the factors that, over time, contribute to bachelor degree attainment for community college?"

What follows is a background and context section as well as a detailed research design. I then present results with a series of tables before offering a discussion and conclusion.

Background and Context

Student Success

A number of studies have explored the factors associated with student success, each with a particular focus or determinant of completion behavior. These determinants include such factors as financial aid (Singell, 2004; DesJardins, Ahlburg, & McCall, 2006a), economic disadvantage (Vignoles & Powdthavee, 2009), academic readiness (see Kerkvliet & Nowel, 2005), academic and social integration (Tinto, 1993), composition of the faculty (Eagen & Jaegar, 2009; Bettinger & Long, 2010), and expected future earnings (Kerkvliet & Nowell, 2005). Results have often been mixed; however, many studies have begun to unearth more information through the use of both richer datasets and more highly sophisticated statistical techniques.

For example, using data collected from the University of Minnesota, DesJardins et al. (2002) estimate the effect of changes in financial aid on student persistence by following students for 22 terms. The authors benefit from the use of a hazard model enabling them to control for time-varying covariates, such as financial aid. After accounting for temporal influences and unobserved heterogeneity, the authors find a positive relationship between different forms of financial aid and student persistence, with debt-free scholarships having the largest impact.

In a more recent study, Powdthavee et al. (2009) focus on the effect of socieconomic gap on student success. The authors compare attrition between students with a low socioeconomic background with their wealthier counterparts. Using a probit model and controlling for self-selection by predicting the likelihood of entering higher education, the authors report that wealthier students and students whose parents hold professional positions have a lower likelihood of dropping out. Overall, however, the authors find that this gap decreases significantly after conditioning on prior academic preparation.

In a study focused on graduation rates, DesJardins et al. (2006b) implement a multiple spells-competing risks model to simultaneously study the instances of stopout, re-enrollment, and graduation. This powerful statistical tool is able to study both the cumulative effects of stopout behavior as well as the effects of student covariates on both stopout and graduation. The authors find that those students who experience one instance of stopping out are more likely to experience subsequent stopout periods and are less likely to graduate. Furthermore, the authors simulate the impact of various student characteristics, such as race, and find that the influence over student performance often attributed to race is actually the result of income, age at entry, and high school preparation. This study is one of the few examples of modeling that allows for multiple events (repeated stopouts) as well as competing risks (stopout and graduation modeled simultaneously).

Studies with a Focus on the Role of Working on Student Success

Early studies focusing on the role of wages on student success have tended to be at a single institution and focused on grade point average outcomes. These studies have yielded incredibly mixed results ranging from negative effects (Astin, 1993; King & Bannon, 2002; Gleason, 1993; Ma & Wooster, 1979; DeSimone, 2008), to no effects (Canabal, 1998; Curtis & Nummer, 1991; Ehrenberg & Sherman, 1987; High, 1999; Kalenkoski & Pabilonia, 2004), and even positive effects (Augenblick, Van De Water & Associates, 1987; Hammes & Haller, 1983; Parsons, 1977). Mixed results have also been found in studies with persistence towards graduation as the outcome. Studies using large-scale, national datasets find that working has a negative effect on persistence (Choy, 2002; Ehrenberg & Sherman, 1987; King, 2002), while some smaller studies find that working has a positive effect (Curtis &

Nummer, 1991; Kulm & Cramer, 2006). In a recent study on the effects of working on student outcomes at liberal arts colleges, Salisbury et al. (2009) find that, overall, students who work suffer no consequences on grade point average or completion outcomes. The authors go on to conclude that working may actually help students in terms of other measures of success, including leadership.

In a study tightly linked to longitudinal working data and student success is that by Jepsen et al. (2010) that explores the stopout behavior of a sample of community college students while conditioning on the wages earned while concurrently enrolled. The authors make use of a single-spell hazard model to study the influence of earnings on initial stopout, finding that a percentage increase in earnings reduces time to stopout with a probability of 1.767%. Their study, while unique in its own right, does not allow students to re-enter the analysis after a first stopout and does not ultimately model degree attainment. I expand upon analysis of Jepsen et al. (2010) by utilizing methods set forth by DesJardins et al. (2006) in order to account for both repeated stopout behavior and the competing risks of stopout and degree attainment. In doing so, I illuminate a clearer picture of the degree attainment process for community college students with a particular focus on wage earned while enrolled. To the best of my knowledge, no other study has undertaken such an investigation.

Research Design

Analytic Model

To conduct this analysis, I utilize a method known as event history analysis (EHA) in order to examine the factors determining whether a student beginning at a community college successfully completes a bachelor's degree. This approach has its roots in the biomedical literature where it was used to study time-to-death investigations. More recently, EHA was brought into the social sciences by Berry and Berry (1990) who used EHA to study the factors associated with state lottery adoptions. Since that time, EHA has been used to study state-level, education-related public policies such as charter school legislation, merit-based student grants, prepaid tuition and savings plans, and student unit-record systems (Renzulli & Roscigno, 2005, Doyle, 2006; Doyle, McLendon, & Hearn, 2005; Hearn, McLendon, & Mokher, 2008).

With a focus on individual students as the unit of analysis as opposed to states, DesJardins (2003), in a methodological piece containing a study on college student departure, demonstrates the power of event history analysis in such a circumstance in that longitudinal data can remedy many of the problems associated with cross-sectional data analysis in that dynamic outcomes in educational research are best explained with variables that are recorded in a way that also reflects change over time. Student degree attainment is a process that takes place over time and can be affected by an array of variables that also change with time. As such, it is ideally suited for event history analysis.

Event history analysis provides at least two benefits over traditional logistic regression (Bennett, 1999; Box-Steffensmeier & Jones, 2004). First, logistic regression can only be used to associate a set of cross-sectional covariates with whether an event occurs. EHA, however, is able to include information not only whether, but also *when* an event (degree attainment) occurs relative to other students. Second, traditional logistic regression techniques omit any cases that have not experienced the event by the end of the time period under study, which could lead to selection bias. In EHA, however, any individual that has not attained a baccalaureate degree by the end of the study period is considered to be a censored observation. This method is then able to incorporate information about uncensored individuals as well as these so-called censored observations in order to obtain unbiased coefficient estimates.

The additional dimensions to this analysis, however, are that of repeated events and competing risks. Community college students may enroll in a given semester, not enroll in the following semester (or several semester), and then reappear enrolled later in postsecondary education. This period of non-enrollment followed by re-enrolling is known as “stopping out” as opposed to “dropping out” whereby the student would never re-enroll. I am interested in modeling the relationship between these events. More specifically, I am interested in the relationship not only between a set of observables and degree attainment, but also the relationship between student stopout behavior and graduation (competing risks). Furthermore, as students can stopout and re-enter higher education more than once I am interested in the relationship between these multiple stopouts and degree attainment (repeated events). As such, l follow a similar procedure to that of Desjardins, Ahlburg, and McCall (2006b) who implement a "multiple spells/competing risks" model.

Model Specification

More formally, I specify the initial model as follows; this model has become the standard to analyze time duration until an event and is known as discrete-time equivalent of the proportional hazards model (Cox, 1972; McCall, 1994):

$$\lambda(t \mid \boldsymbol{x}(t), \theta) = \Pr(T = t \mid T \geq t-1, \boldsymbol{x}(t), \theta)$$
$$= 1 - \exp\left(-\exp(\alpha(t) + \boldsymbol{x}(t)'\boldsymbol{\beta})\,\theta\right)$$

The vast majority of earlier studies have modeled duration only until a single event occurs. For instance, DesJardins et al. (1999, 2002) estimate the probability of first stopout where $\Pr(T = t \mid T \geq t-1, \boldsymbol{x}(t), \theta)$ is the probability of an invidiual student stopping out in discrete period t; T is a discrete variable measure the number of terms of continuous enrollment until stopout occurs; $\boldsymbol{x}(t)$ is a vector of covariates for each student and $\boldsymbol{\beta}$ is a vector of the coefficients estimated for $\boldsymbol{x}(t)$; θ is an unobserved covariate assumed to be orthogonal to $\boldsymbol{x}(t)$; and $\alpha(t)$ is a time-varying constant-term interpreted as the base-line hazard rate or base-line risk of experiencing the event.

The modeling of multiple durations (as a result of stopout behavior) adds another dimension to the model by incorporating information on the history of previous enrollment spells. In other words, I am able to incorporate information on multiple enrollment spells (separated by a period of stopout). This information includes both the number and length of stopout periods. In a statistical model, this involves adding an index k and the term $\mathbf{h}_{t\text{-}1}$ (representing the length of previous durations) that can then affect future durations. I define this model as:

$$\lambda_k(t_k|\, \boldsymbol{x}(t_k), \boldsymbol{h}_{k-1}, \theta_k) = \Pr(T_k = t_k \mid T_k \ \geq t_k - 1, \boldsymbol{x}(t_k), \boldsymbol{h}_{k-1}, \theta_k)$$

$$= 1 - \ \exp\left(- \exp(\alpha_k(t_k) + \ \boldsymbol{x}(t_k)'\boldsymbol{\beta_k} + \ \boldsymbol{h}'_{k-1}\boldsymbol{\delta_k})\, \theta_k\right)$$

where $\boldsymbol{\delta_k}$ is a vector of parameters that guage the influence of past variables.

Finally, I model not only stopout behavior, but also the main event of interest: graduation. As such, I add a competing risks component to the model such that Y_k is a variable that equals j if the enrollment spell ended for reason j. In the case of this analysis j consists of only two options: stopout or graduation. In periods of enrollment, I define Y_k to be equal zero. Thus, a final model is specified as:

$$\lambda_k^j(t_k|\, \boldsymbol{x}(t_k), \boldsymbol{h}_{k-1}, \theta_k^j) = \Pr(T_k = t, Y_k \mid T_k \ \geq t_k - 1, \boldsymbol{x}(t_k), \boldsymbol{h}_{k-1}, \theta_k^j)$$

$$= 1 - \ \exp\left(- \exp\left(\alpha_k(t_k) + \ \boldsymbol{x}(t_k)'\boldsymbol{\beta}_{\boldsymbol{k}}^j + \ \boldsymbol{h}'_{k-1}\boldsymbol{\delta}_k^{\boldsymbol{j}}\right) \theta_k^j\right)$$

where $\boldsymbol{\beta}_{\boldsymbol{k}}^j$ and $\boldsymbol{\delta}_k^{\boldsymbol{j}}$ estimate the effect of $\boldsymbol{x}(t_k)$ and $\boldsymbol{h}_{k-1}$on the likelihood of that the enrollment spell ends at time t due to the jth reason. This approach allows not only for the individuals factors influencing degree completion ($\boldsymbol{x}(t_k)$) with a focus on wages, but also accounts for the competing risk of stopout behavior and the repeated events of re-enrollment. Both of these behaviors are common to the experiences of community college students and will undoubtedly better inform the field after taking into consideration the role of stopout behavior, re-enrollment, and invidiual characteristics such as wages earned while enrolled.

Data

To conduct this analysis, I follow a cohort of students who initially began at the community college in the fall 2000 semester. I construct the time-varying outcome variable in a multinomial fashion indicating whether a student is (0) currently enrolled in postesecondary education (1) stopping out, or (2) reached graduation. Thus, the dataset is in the form of a student-semester format whereby each student has an individual record for every semester he or she is enrolled. Additionally, data on the length of time (in semesters) spent unenrolled is calculated using enrollment data. Other variables include student characteristics: race and sex; high school academic preparation: whether the student took a trigonometry or AB/IB course, and performance on the state math exam; high school text variables: enrollment and pupil-teacher ratio; economic variables: economic status (whether a student qualified for a free or reduced lunch program in high school and county employment rates; wages; and two postsecondary characteristics: percentage of tenured faculty and percentage of part-time faculty. Data on logged wages and postsecondary characteristics are time-varying. As an additional control, I include an indicator for whether the student is enrolled in a four-year institution in any given semester.

Data on race, sex, economic status, AP/IB coursework, trigonometry coursework, dual enrollment, math test score, and faculty information are available from the TSMP. Data on unemployment and wage data are available from the Texas Comptroller. All remaining community context variables are available from the

CCD. Descriptive statistics for the semester of initial enrollment are provided in Table 14.

Table 14
Descriptive Statistics for Event History Analysis of Degree Completion at Initial Enrollment

	Mean	Std. Dev.
Bachelor's Degree		
Completion	0.162	0.369
Student Characteristics		
Hispanic	0.319	0.466
Black	0.100	0.299
Asian	0.024	0.153
Other	0.013	0.111
Male	0.460	0.498
HS Academic Prep		
Trig Course	0.273	0.445
AP/IB Course	0.264	0.441
Math Score	46.275	11.436
HS Context		
HS Enrl.	1552.543	919.859
HS Pupil:Teacher	14.447	2.544
Economic Situation		
Economic Status	0.249	0.432
County Unemployment	4.642	1.616
Wages		
Wage (logged)	5.042	3.454
PS Characteristics		
PS Percent Tenure	0.063	0.110
PS Percent Part-time	0.389	0.145
N	38222	

Results

The results are organized into three broad categories: a flow analysis, a focus on graduation, and then multiple iterations of the full model examining the factors influencing stopout, re-enrollment, and eventual degree attainment. In the flow analysis, I present the overall enrollment patterns for community college students. Then, I present a basic model predicting graduation as well as more complex models that condition upon different enrollment patterns. Finally, I present models that examine the factors influencing initial stopout, the likelihood of returning, and then repeat this pattern for another iteration allowing for a more flexible and informative model of overall degree attainment. Following the results section, I offer a discussion of the most prominent findings.

Flow Analysis

To better understand the enrollment patterns of community college students, I first present a flow analysis detailing the number of students who stop out, drop out, re-enroll, and/or graduate; these patterns are depicted in Figure 4. The vast majority of community college students (94%) experience at least one period of non-enrollment, including those students who are successful in eventually completing a bachelor's degree. Indeed, of those students who eventually complete a bachelor's degree, only 13% do so without first stopping out. While most students experience at least one session of non-enrollment, many students return; of those students who initially stop out, 72% return for a second period of enrollment. During this second period of enrollment, the majority (76%) of all who students who compete a bachelor's degree do so without an additional period of non-enrollment. After stopping out after a second enrollment spell, the percentage of returning students completing a bachelor's degree decreases substantially. Finally, while roughly 84% of students have failed to complete a bachelor's degree within the six-year timeframe, 21% of these students remain enrolled at the end of the timeframe.

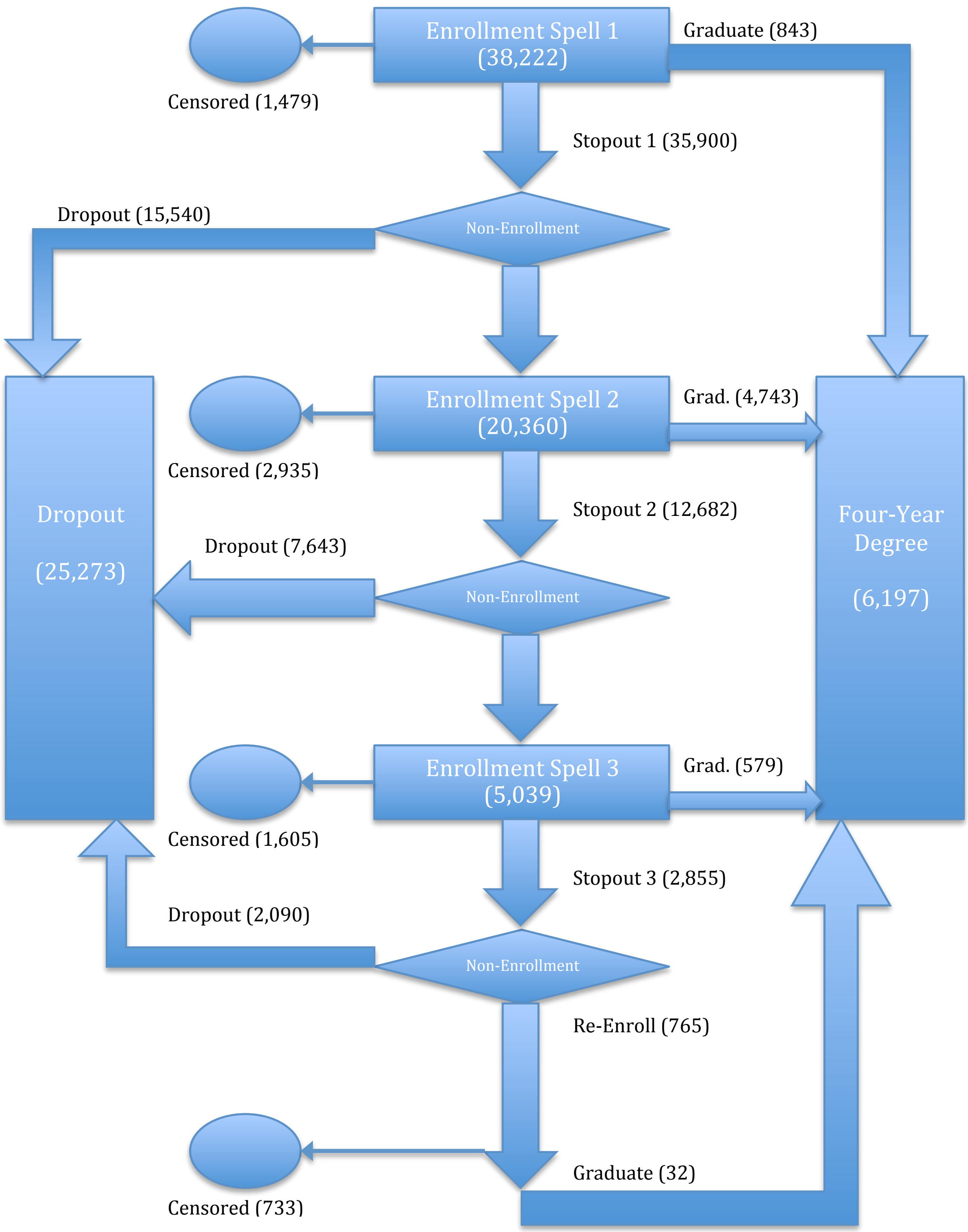

Figure 4: Flow Analysis for Degree Attainment

A Focus on Graduation

What could explain these enrollment patterns? To answer this sweeping question, I first turn to a basic event history model predicting overall graduation using pre-college, student-level covariates as well as wage and institutional data; I allow for re-enrollment, but do not yet account for information about the length of previous enrollment spells. Results from this analysis are presented in Table 15. For ease of interpretation, I present both the coefficients as well as the transformed change on the odds of graduation. Both Hispanic and Black students are less likely to graduate, as are males. In addition, all of the high school academic preparation variables have a positive impact on graduation while the economic factors show a negative impact. Not surprisingly, the estimate for the indicator of being at four-year institution is incredibly large, statistically significant, and positive; however, perhaps more interestingly, the percent tenure shows a positive estimate and the percent part-time shows a negative estimate. Wages, even in this early model, seem to disproportionately—and negatively—affect overall graduation. For a percent increase in wages earned while concurrently enrolled, we see nearly a four percent decrease in the odds of completing a degree. While these estimates begin to shed light on the graduation story of community college students, I have already shown that the vast majority of students experience spells of non-enrollment. As such, I now turn to graduation models that examine the factors affecting degree attainment allowing for different enrollment patterns.

Table 15
Event History Analyis Predicting Overall Graduation

		Estimate [SE]	Change in Odds
Student Characteristics			
	Hispanic	-0.4594***	-37%
		[0.04]	
	Black	-0.2214***	-20%
		[0.06]	
	Asian	0.0037	0%
		[0.07]	
	Other	-0.0777	-7%
		[0.12]	
	Male	-0.4091***	-34%
		[0.03]	
HS Academic Prep			
	Trig Course	0.2175***	24%
		[0.03]	
	AP/IB Course	0.1591***	17%
		[0.03]	
	Math Score	0.0194***	2%
		[0.00]	
HS Context			
	HS Enrl	0.0229	2%
		[0.02]	
	HS Pupil:Teacher	-0.009	-1%
		[0.01]	
Econoimc Situation			
	Economic Status	-0.2920***	-25%
		[0.04]	
	County Unemployment	-0.0263**	-3%
		[0.01]	
Wages			
	Wages (logged)	-0.0368***	-4%
		[0.00]	
PS Characteristics			
	Four-Year Institution	1.7585***	480%
		[0.14]	
	PS Percent Tenure	0.6585***	93%
		[0.12]	
	PS Percent Part-time	-0.6915***	-50%
		[0.13]	
Constant		-79.2155***	-100%
		[4.50]	
chi2		25664.0705	

** p<0.05, ** p<0.01, *** p<0.001*

Table 16 depicts graduation as an outcome conditional on different enrollment patterns. The first column is a replication of Table 15, for comparison purposes. Column 2 depicts graduation with no stops while Columns 3 and 4 depict graduation with one and two stops, respectively. With graduation in the first enrollment spell without any stops (column 2) being so rare, it is not surprising that so many of the student-level covariates shown to be predictive in the first model are no longer statistically significant. It appears as though remaining continuously enrolled, in itself, is the strongest predictor of whether a student graduates. Males, however, show a lower likelihood of graduating, even if remaining continuously enrolled.

The factors influencing graduation for students with one stop out period (column 3) are remarkably similar to those in the overall model (column 1). Again, however, this is not incredibly surprising given that the vast majority of community college students who successfully complete a bachelor's degree do so after one period of non-enrollment. In this model, however, I now include a covariate for the length of time (in semesters) a student had previously spent non-enrolled. In other words, I control for the number of semesters between the semesters in which a student is actively enrolled. The estimate for this variable is statistically significant and negative (though small), suggesting that students who had previously been non-enrolled are less likely to graduate. Finally, for students who experience two period of non-enrollment, there is a stronger effect of the length of time previously spent non-enrolled, with 28% and 21% negative changes in the odds for the semester spent non-enrolled in non-enrollment periods 1 and 2, respectively. Just as in the basic model, percent changes in wages appear to have a negative and disproportional relationship to graduation. With these estimates in mind, I turn now to models that incorporate stopout behavior and allow for the copeting risk of stopout and graduation.

Table 16
Event History Analyis Predicting Graduation by Enrollment History

	1 Overall Graduation		2 Graduation with No Stops		3 Graduation with One Stop		4 Graduation with Two Stops	
	Estimate [SE]	Change in Odds	Estimate [SE]	Change in Odds	Estimate [SE]	Change in Odds	Estimate [SE]	Change in Odds
Student Characteristics								
Hispanic	-0.4594***	-37%	-0.1158	-11%	-0.4919***	-39%	-0.6101***	-46%
	[0.04]		[0.10]		[0.05]		[0.13]	
Black	-0.2214***	-20%	0.1237	13%	-0.2640***	-23%	-0.4013*	-33%
	[0.06]		[0.15]		[0.07]		[0.20]	
Asian	0%	0%	-0.1081	-10%	0.092	10%	0.3411	41%
	[0.07]		[0.18]		[0.09]		[0.24]	
Other	-8%	-7%	-0.1229	-12%	-0.0214	-2%	0.0456	5%
	[0.12]		[0.32]		[0.14]		[0.31]	
Male	-0.4091***	-34%	-0.1945**	-18%	-0.4007***	-33%	-0.3394***	-29%
	[0.03]		[0.08]		[0.03]		[0.09]	
HS Academic Prep								
Trig Course	0.2175***	24%	-0.0188	-2%	0.2706***	31%	-0.0088	-1%
	[0.03]		[0.08]		[0.03]		[0.10]	
AP/IB Course	0.1591***	17%	0.0261	3%	0.1582***	17%	0.2200*	25%
	[0.03]		[0.08]		[0.03]		[0.10]	
Math Score	0.0194***	2%	0.0222***	2%	0.0149***	2%	0.0132*	1%
	[0.00]		[0.01]		[0.00]		[0.01]	
HS Context								
HS Enrl	2%	2%	0.0228	2%	-0.0014	0%	0.0361	4%
	[0.02]		[0.06]		[0.02]		[0.07]	
HS Pupil:Teacher	-1%	-1%	-0.0196	-2%	-0.0009	0%	0.0064	1%
	[0.01]		[0.02]		[0.01]		[0.03]	
Economic Situation								
Economic Status	-0.2920***	-25%	-0.0456	-4%	-0.3278***	-28%	-0.2577	-23%
	[0.04]		[0.10]		[0.05]		[0.14]	
County Unemployment	-0.0263**	-3%	-0.0418	-4%	-0.0153	-2%	0.0017	0%
	[0.01]		[0.03]		[0.01]		[0.03]	
Wages								
Wages (logged)	-0.0368***	-4%	-0.0313**	-3%	-0.0340***	-3%	-0.0487***	-5%
	[0.00]		[0.01]		[0.00]		[0.01]	
PS Characteristics								
Four-Year Institution	1.7585***	>100%	1.3945***	>100%	1.7129***	>100%	2.5680***	>100%
	[0.14]		[0.36]		[0.16]		[0.48]	
PS Percent Tenure	0.6585***	93%	.4291***	54%	.8980***	145%	.9271***	153%
	[.12]		[.39]		[.18]		[.44]	
PS Percent Part-time	-0.6915***	-50%	-.5509***	-42%	-0.7144***	-51%	-1.2974***	-73%
	[0.13]		[0.38]		[0.15]		[0.42]	
Stopout Length								
Stop Out Length 1					-0.0250*	-2%	-0.3253***	-28%
					[0.01]		[0.06]	
Stop Out Length 2							-0.2347***	-21%
							[0.05]	
Constant	-79.2155***	-100%	-163.1274***	-100%	-64.2024***	-100%	-63.6978*	-100%
	[4.50]		[47.13]		[4.46]		[29.90]	
chi2	2566407%		5301.4459		18105.73		2770.7921	

** p<0.05, ** p<0.01, *** p<0.001*

Stopout Behavior as a Competing Risk with Graduation

The likelihood of completing an undergraduate degree without any stopout behavior is very low for community college students. As such, I model only the factors influencing stopout in the first iteration of the analysis; Table 17 presents these estimates for initial stopout behavior. Interestingly, there is no statistically significant difference between White and Hispanic students with respect to initial stopout. Surprisingly, students identified as free or reduced lunch eligible are less likely to stopout (and, thus, more likely to remain enrolled). Furthermore, only the trigonometry course indicator is significant with respect to academic preparation—those students who took trigonometry are less likely to stopout. Also, those students who successfully enrolled in a four-year institution after beginning in a community college are less likely to stopout. Again, however, working appears to have a negative impact on educational outcomes, with a percent increase in wages earned resulting in a disproportional increase in the odds of stopping out.

Table 17
Event History Analyis Predicting Initial Stopout

	Estimate [SE]	Change in Odds
Student Characteristics		
Hispanic	0.0114	1%
	[0.02]	
Black	0.0719**	7%
	[0.03]	
Asian	-0.1786***	-16%
	[0.05]	
Other	0.0532	5%
	[0.07]	
Male	-0.0186	-2%
	[0.02]	
HS Academic Prep		
Trig Course	-0.1291***	-12%
	[0.02]	
AP/IB Course	-0.0278	-3%
	[0.02]	
Math Score	0.0013	0%
	[0.00]	
HS Context		
HS Enrl	-0.0091	-1%
	[0.01]	
HS Pupil:Teacher	-0.002	0%
	[0.00]	
Economic Situation		
Economic Status	-0.0382	-4%
	[0.02]	
County Unemployment	-0.002	0%
	[0.01]	
Wages		
Wages (logged)	0.0327***	3%
	[0.00]	
PS Characteristics		
Four-Year Institution	-0.6410***	-47%
	[0.05]	
PS Percent Tenure	.5491***	73%
	[.03]	
PS Percent Part-time	-0.1152*	-11%
	[0.06]	
Constant	2.0545***	
	[0.08]	
chi2	1495.9234	

** p<0.05, ** p<0.01, *** p<0.001*

After students have initially stopped out, they have two options: (1) re-enroll in a subsequent term in the analysis or (2) dropout altogether (never return during the study time period). As such, I next model the factors associated with never returning to higher education after one period of non-enrollment; Table 18 presents these estimates. In other words, I model the observable characteristics that are associated with never re-enrolling after an initial spell of non-enrollment. Again, there is no statically significant difference between White and Hispanic students; Black students, however, are more likely to never re-enroll, while Asian students are less likely. Males are also more likely to never re-enroll. Students with strong indicators of academic preparation are less likely to never re-enroll (and, thus, more likely to re-enroll in a later semester). Additionally, those students who successfully enrolled in a four-year institution are less likely to never re-enroll. Increased earnings, again, seem to inhibit success as a percent increase in earnings is shown to have a positive impact on the odds of never re-enrolling. Collectively, the factors influencing never re-enrolling appear to be similar to the factors predicting overall graduation, though opposite in direction. In both instances, increases in wages appear to decrease the likelihood of academic success. Of those students who return for a second period of enrollment, there is substantially more variation in their eventual outcomes. These students either: (1) stop out again, (2) graduate or (3) remain continuously enrolled. Using option (3) as a base comparison group, I next model the competing risks of stopping out again and graduating for students in their second enrollment spell; these results are presented in Table 19.

Table 18
Logistic Regression: Risk of Never Returning After 1 Stopout

	Estimate [SE]	Change in Odds
Student Characteristics		
Hispanic	0.0009	0%
	[0.02]	
Black	0.0961**	10%
	[0.03]	
Asian	-0.2632***	-23%
	[0.06]	
Other	-0.1249	-12%
	[0.08]	
Male	0.1264***	13%
	[0.02]	
HS Academic Prep		
Trig Course	-0.2618***	-23%
	[0.02]	
AP/IB Course	-0.0918***	-9%
	[0.02]	
Math Score	-0.0071***	-1%
	[0.00]	
HS Context		
HS Enrl	-0.0987***	-9%
	[0.01]	
HS Pupil:Teacher	-0.0015	0%
	[0.00]	
Economic Situation		
Economic Status	-0.0281	-3%
	[0.02]	
County Unemployment	0.0086	1%
	[0.01]	
Wages		
Wages (logged)	0.0230***	2%
	[0.00]	
PS Characteristics		
Four-Year Institution	-2.0615***	-87%
	[0.06]	
PS Percent Tenure	-0.3464***	-31%
	[.07]	
PS Percent Part-time	-0.4613***	-37%
	[0.07]	
Constant	8.9696***	>100%
	[0.17]	
chi2	34751.5517	

** p<0.05, ** p<0.01, *** p<0.001*

Table 19 shows the first two multiple spells-competing risks models. Hispanic students are show to be less likely to stop out, yet also less likely to graduate; Hispanic students, it appears, are the most likely to remain continuously enrolled after returning for a second enrollment spell. Black students, however, are both more likely to stop out again and less likely to graduate; males follow a similar pattern. Measures of pre-college academic preparation behave in a manner consistent with previous models: improving academic success by decreasing the likelihood of another stop out period and increasing the likelihood of graduation. Economic factors do not appear to be an influence on stop out, yet while the free or reduced lunch designation of the student has a negative effect on graduation, the county unemployment where the student went to high school has a positive effect. Successfully transitioning to a four-year institution also has a positive effect on academic outcomes: students enrolled in a four-year institution are less likely to stop out and (not surprisingly) more likely to graduate. Finally, wages tell precisely the opposite story, though greater magnitude than in previous models—while a percent increase in wages has a roughly 4% effect on the odds of stopping out again, we see a whopping 13% decrease in the odds of graduation.

Table 19
Risks of Stopout and Graduation in Enrollment Period 2

	Stopout		Graduation	
	Estimate [SE]	Change in Odds	Estimate [SE]	Change in Odds
Student Characteristics				
Hispanic	-0.0718*	-7%	-0.6774***	-49%
	[0.03]		[0.05]	
Black	0.1447***	16%	-0.7147***	-51%
	[0.04]		[0.08]	
Asian	-0.2268**	-20%	-0.0478	-5%
	[0.09]		[0.11]	
Other	-0.2133	-19%	-0.2993	-26%
	[0.11]		[0.18]	
Male	0.2047***	23%	-0.4295***	-35%
	[0.02]		[0.04]	
HS Academic Prep				
Trig Course	-0.2384***	-21%	0.7365***	109%
	[0.03]		[0.04]	
AP/IB Course	-0.1135***	-11%	0.3836***	47%
	[0.03]		[0.04]	
Math Score	-0.0083***	-1%	0.0327***	3%
	[0.00]		[0.00]	
HS Context				
HS Enrl	-0.1255***	-12%	0.0729*	8%
	[0.02]		[0.03]	
HS Pupil:Teacher	-0.0018	0%	-0.0118	-1%
	[0.01]		[0.01]	
Economic Situation				
Economic Status	0.0319	3%	-0.4055***	-33%
	[0.03]		[0.06]	
County Unemployment	-0.0108	-1%	0.0566***	6%
	[0.01]		[0.01]	
Wages				
Wages (logged)	0.0227***	2%	-0.0748***	-7%
	[0.00]		[0.01]	
PS Characteristics				
Four-Year Institution	-1.3686***	-75%	1.1154***	>100%
	[0.08]		[.03]	
PS Percent Tenure	-0.7435***	-52%	-0.4548**	-36%
	[.06]		[0.17]	
PS Percent Part-time	-0.3470***	-29%	-0.2301	-21%
	[0.09]		[0.15]	
Stopout Length				
Stop Out Length 1	0.0421***	4%	-0.1414***	-13%
	[0.01]		[0.01]	
Stop Out Length 2				
Constant	-5.9916***		17.8081	
	[0.19]		[24.28]	
chi2	27107.3535			

** p<0.05, ** p<0.01, *** p<0.001*

After a second enrollment spell ends by another stop out period, students are, again, in a situation with two options: (1) never return to higher education or (2) enroll in a later semester. I follow students a total of three enrollment spells and, thus, Table 20 reports the risks of never returning to higher education after a second period of non-enrollment. Interestingly, very few variables in the model are statistically significant. Asian students are less likely to never re-enroll, though no other differences by race or sex are observed. Students at a four-year institution are less likely to never re-enroll, suggesting that students who successfully make the transition to a four-year institution are more likely to return to higher education, even after two stop out periods. Also, the length of a student's first stop out period is positively related to the odds of never re-enrolling after a second stop out period. This model shows no statistically significant relationship between the odds of never re-enrolling and wages earned. For those students who do re-enroll, however, I present one final model that shows the competing risks of stop out and graduation for students in their third enrollment period.

Table 20
Logistic Regression: Risk of Never Returning After 2 Stopouts

	Estimate [SE]	Change in Odds
Student Characteristics		
Hispanic	-0.0414	-4%
	[0.04]	
Black	0.0214	2%
	[0.06]	
Asian	-0.4470***	-36%
	[0.12]	
Other	-0.0409	-4%
	[0.15]	
Male	0.0539	6%
	[0.03]	
HS Academic Prep		
Trig Course	-0.0771	-7%
	[0.04]	
AP/IB Course	0.0219	2%
	[0.04]	
Math Score	0.0017	0%
	[0.00]	
HS Context		
HS Enrl	-0.0462	-5%
	[0.03]	
HS Pupil:Teacher	0.0006	0%
	[0.01]	
Economic Situation		
Economic Status	-0.0602	-6%
	[0.04]	
County Unemployment	0.0209	2%
	[0.01]	
Wages		
Wages (logged)	0.0056	1%
	[0.00]	
PS Characteristics		
Four-Year Institution	-0.9981***	-63%
	[0.11]	
PS Percent Tenure	-.1923***	-17%
	[.09]	
PS Percent Part-time	-0.3285**	-28%
	[0.13]	
Stopout Length		
Length of Stopout 1	0.3591***	43%
	[0.01]	
Constant	31.1124***	>100%
	[1.33]	
chi2	62137	
** p<0.05, ** p<0.01, *** p<0.001*	13816.7135	

Table 21 presents results for the competing risks-multiple spells model from enrollment period 3. As was the case in the model for enrollment period 2, Hispanic students are less likely to both stop out as well as graduate. While Black students are less likely to graduate, there is no statistically significant difference for Black students with respect to stop out. Males, however, remain more likely to stop out and less likely to graduate. Variables for high school academic preparation behavior act in similar ways as in previous models, both decreasing the odds of an additional stop out and increasing the odds of graduation. Interestingly, students qualifying for free or reduced lunch have decreased odds of stopping out, yet no effect on graduation. Just as before, those successfully transitioning to a four-year institution have increased odds of academic success: less likely to stop out and more likely to graduate. Finally, the length of time spent stopped out in the previous two non-enrollment spells has a negative effect on an additional stop out period, yet the length of time spent non-enrolled in the second non-enrollment spell also has a negative effect on graduation.

Table 21
Risks of Stopout and Graduatin in Enrollment Period 3

	Stopout		Graduation	
	Estimate [SE]	Change in Odds	Estimate [SE]	Change in Odds
Student Characteristics				
Hipsanic	-0.1304*	-12%	-0.5434***	-42%
	[0.05]		[0.13]	
Black	-0.0225	-2%	-0.5448**	-42%
	[0.07]		[0.21]	
Asian	-0.4598**	-37%	0.4276	53%
	[0.17]		[0.26]	
Other	0.0638	7%	0.2804	32%
	[0.19]		[0.37]	
Male	0.1732***	19%	-0.3374***	-29%
	[0.04]		[0.10]	
HS Academic Prep				
Trig Course	-0.2823***	-25%	0.3818***	46%
	[0.05]		[0.11]	
AP/IB Course	-0.2016***	-18%	0.4284***	53%
	[0.05]		[0.10]	
Math Score	-0.0102***	-1%	0.0396***	4%
	[0.00]		[0.01]	
HS Context				
HS Enrl	-0.0363*	-4%	0.0847**	9%
	[0.01]		[0.03]	
HS Pupil:Teacher	0.006	1%	-0.0502***	-5%
	[0.01]		[0.01]	
Econoimc Situation				
Economic Status	-0.1716***	-16%	-0.0183	-2%
	[0.03]		[0.07]	
County Unemployment	-0.0216	-2%	-0.0142	-1%
	[0.01]		[0.03]	
Wages				
Wages (logged)	0.1456**	16%	-0.2616	-23%
	[0.05]		[0.15]	
PS Characteristics				
Four-Year Institution	-0.8924***	-59%	1.1123***	204%
	[.14]		[.08]	
PS Percent Tenure	-1.0524***	-65%	-0.9777*	-62%
	[0.16]		[0.44]	
PS Percent Part-time	-0.5440***	-42%	-0.4443	-36%
	[0.16]		[0.39]	
Stopout Length				
Stop Out Length 1	-1.2631***	-72%	-0.0375	-4%
	[0.04]		[0.04]	
Stop Out Length 2	-0.6363***	-47%	-0.1683***	-15%
	[0.03]		[0.04]	
Constant	6.5510***	>100%	18.4019	>100%
	[0.22]		[135.71]	
chi2	12054.5006			

** p<0.05, ** p<0.01, *** p<0.001*

Discussion

The results of this analysis have provided for at least five points of discussion. First, racial groups differentially experience the community college enrollment and graduation process. Second, the impact of pre-college factors yields strong predictive power of student success in the early stages of the enrollment story, yet has little effect later on. Third, and not completely surprising, students who are successful in transferring to a four-year institution are more likely to graduate, but are also more likely to remain enrolled and return to higher education after periods of non-enrollment. Fourth, wages earned tend to inhibit overall student success. Fifth, prior enrollment behavior tends to influence later stop out and graduation behavior. What follows is a brief discussion of each.

Hispanic students represent a sizeable portion (32%) of the sample, yet are shown to have lower odds of degree completion than their white peers. In several cases, however, Hispanic students show no statistically significant difference than white students—in the cases of initial stop out and never returning after one or two periods of non-enrollment. Furthermore, Hispanic students are *less* likely than white students to experience a second stop out period. Hispanic students are likely to re-appear in the higher education system after stop out and remain enrolled; however, graduation still suffers. Policy implementation seems to be warranted at allowing for flexibility in re-enrollment and a push for increased graduation after students, and particularly Hispanic students, re-enter the system. The story for Black students, however, is not the same. Black students are less likely to graduate overall, but also more likely to stop out and never re-enroll in higher education. Unlike Hispanic students, Black students appear to depart from higher education and never return. Again, it appears as though programs designed to encourage re-enrollment seem to be warranted.

High school academic preparation in the form of a trigonometry course, an AP or IB course, and the state math exam score have a strong relationship with overall graduation rates as well as the propensity to remain enrolled and re-enroll after an initial stop out. Later in the process, however, academic preparation appears to less of an impact on the odds of returning after two stop out periods. Students with a strong academic background from high school behave no differently than other students when it comes to enrolling in a third enrollment period. The key, it seems, is to keep these academically strong students enrolled with little, or no, periods of stop out behavior. Policy implementation appears to be warranted at keeping these students enrolled.

Students at a four-year institution are (not surprisingly) more likely to graduate, but are also more likely to stay enrolled and more likely to re-enroll in the event of a stop out period. Perhaps those students successful in transfer are able to "see the light at the end of the tunnel" in terms of degree completion and, even after a period of non-enrollment, are more likely to re-enroll. The successful transition between the two and four-year sectors, it appears, is important not only in graduating students, but also in keeping students in the pipeline towards eventual graduation.

Overall, wages appear to inhibit the academic success of students. This finding, however, must be tempered with the knowledge that working while continuously enrolled is the reality of many community college students. Policies going so far as to discourage working altogether may not be feasible; however, policy geared at reducing the number of hours students work while enrolled may increase the overall graduation rate of community college students. This is especially important as the impact of working on inhibiting student success appears to increase with time and with additional periods of non-enrollment—the more times a student stops out, the more less likely he or she is to graduated while continuing to work.

Finally, previous periods of non-enrollment have an effect on future academic success and enrollment trends, though this effect is not always consistent. Students with longer previous non-enrollment periods are more likely to never return in future non-enrollment spells; however, the length of time spent non-enrolled has a different effect if a student is successful in re-enrolling. Students with longer previous non-enrollment spells are less likely to experience another stop out period. Perhaps these students who have returned for a third enrollment spell have a strong determination to succeed, despite the amount of time spent previously non-enrolled. Again, policy implementation geared at facilitating re-enrollment appears to be warranted.

Conclusions

Working is a large part of the lives of community college students, yet appears to inhibit overall academic success in terms of graduation and the propensity to re-enroll after a period of non-enrollment. The resounding message is one of "work less and study more;" however, this is simply not an option for many community college students. How could we improve student success with the understanding that many students are working? One mechanism through which this may be possible, and one limitation of this study in that it is not included, is financial aid. Future analyses would benefit from the use of financial aid data as well as earned wages to provide a more complete picture of the college completion process for community college students.

The journey to a four-year degree for those students beginning in the community college is undoubtedly a long one, marked by periods of transition and change. Through the use of a competing risks/multiple spells model I have shown the effect of race, sex, academic preparation, high school and economic context, wages, post-secondary characteristics, and previous enrollment histories on student success. While many factors influence overall success, it appears that those students who are working while continuously enrolled experience lower rates of academic success. Put differently, these students are working hard for the degree, yet not succeeding in attaining it.

CHAPTER V

GENERAL DISCUSSION, CONCLUSIONS,
AND DIRECTIONS FOR FUTURE RESEARCH

Introduction

The three essays comprising this dissertation were ordered intentionally to reflect (1) the impact of full time enrollment, (2) whether initial enrollment in a community college inhibits degree attainment after successful transfer, and (3) the overall completion story, with a focus on working while enrolled. This purposive ordering was done to reflect the clear chronological order of (1) to (2) and the overarching story contained in (3). In this final chapter, I review the key findings from each of the essays as well as discuss their policy impacts. I then summarize contributions to theory and practice, provide directions for future research and, finally, and offer a concluding note on the very title of this dissertation—The Role of the Community College in Texas.

Summary of Findings and Implications

The Impact of Full Time Enrollment on Successful Transfer

Community college students who enroll full time in their first semester are more likely to transfer to a four-year institution. This finding remains constant across the statistical techniques to remove inherent sample selection bias as well as rigorous sensitivity analyses. Perhaps state policy efforts designed to encourage, incentivize, or require full time enrollment may very well increase student success for community college students. At one end of the spectrum, encouraging students to enroll full time via financial aid simulations or simply demonstrating the time it would take to complete a degree when earning less than twelve credits a semester certainly seems reasonable. At the far end of the spectrum, however, requiring students to enroll full time may very well serve to decrease overall access to higher education as placing such a harsh restriction on enrollment requirements would most certainly eliminate many of the I have included in this analysis students (first time enrollees immediately out of high school) and would most definitely affect the thousands of other students in a community college (older, re-enrolling, or lifelong learning students).

The key then, it seems, is to find a balance somewhere in the middle. Perhaps answers lie in incentivizing full time enrollment through financial support mechanisms. For example, perhaps students could receive twelve credits at the cost of nine or perhaps a scaled discounting system could be offered for each additional credit. Also, many community colleges have additional programs in place to facilitate full time enrollment such as study groups, childcare, and flexible course hours. In direct connection to the mediating issue of student engagement, Braxton, Hirschy, and McClendon (2004) recommend the use of communities of learning by which community college students would attend blocks of courses together. Enrolling full time appears to have a clear link in successful transfer—the challenge now is to best make this a viable option for community college students.

The Impact of Beginning at a Community College on Baccalaureate Degree Attainment

For some time now, the democratization/dispersion debate of the role of the community college has been going on. As has been the case with more contemporary, empirical studies investigating this relationship, I find less of a dispersion effect after conditioning on a myriad of institutional pre-college characteristics, postsecondary factors, and the composition of a sample that most clearly creates a comparison groups—those students who successfully transferred compared to those who are entering their third year in the four-year sector. On average, the effect of beginning in a community college becomes less strong and begins to approach zero; however, this is not the case for minority students.

The 14.9% and 35.9% graduation differential for Hispanic and Black students, respectively, when compared to peers of their own race in the four-year sector is alarming, particularly for Black students. What remains unclear, however, is whether the community college is merely underpreparing students, or if there is momentum in the four-year sector that impacts graduation for Black students. Perhaps minority students benefit more from the student engagement often present in stronger magnitude at the four-year school. Furthermore, without early integration and support, Black students may struggle in the completion of a baccalaureate degree. Perhaps community colleges would benefit from taking additional efforts to better integrate Black students into the community of students.

The Impact of Wages Earned on Overall Degree Attainment

The enrollment story for community college students is often one of working while concurrently enrolled. Furthermore, the pathway to a baccalaureate degree for community college students is one marked by periods of non-enrollment. As the vast majority of community college students will experience an initial stopout, policy interventions, at minimum, seem to be warranted at providing for ease of re-enrollment. Perhaps community colleges could provide programs by which students would receive additional counseling after returning after a period of non-enrollment.

While a strong message of "work less and study more" is prevalent in the findings, this is an option that may simply not be an option for community college students. Much like the policy suggestions from the first essay, however, perhaps policy interventions could be designed to encourage, incentivize, or require students not to be working full-time while enrolled. Again, while the far right end of the spectrum seems to be impossible, there may be other interventions to decrease the workload required by students such as providing financial incentives.

Summary of Contributions to Theory and Practice

This dissertation has informed both theory and practice through its three-pronged approach aimed at better understanding the role of the community college in Texas. With a clearer understanding of the impact of full time enrollment on successful transfer, Texas, and other states like it, will be able to make a more informed decision on policy initiatives that encouraging full time enrollment. In addition, these results lend credence to the notion that full time enrollment may lead to deeper engagement and, ultimately, to increased transfer. Additionally, I have illuminated findings that speak, on average, to challenging, yet tempering, the democratization effect, yet show how these results are differentially experienced by race. Finally, I have demonstrated that, similar to theory and other studies, increased working hours results in decreased degree attainment.

Unlike other analyses, this project has the added benefit of using a vast dataset and incorporating such information as pre-college characteristics, postsecondary factors, and employment data while students are enrolled. Given the composition of the state and its vast higher education landscape, it is likely that lessons that lessons learned in Texas will be applicable to other systems, as well. Perhaps Texas will be the next state to step into the policy limelight behind Connecticut, California, and New York as innovators of policies aimed increasing the success of community college students.

Directions for Future Research

Four main areas for future research came up in the completion of this work: (1) the inclusion of financial aid information, (2) conducting a similar study in another state or context, (3) further investigating differential outcomes by race on a smaller scale using mixed methods, and (4) examining outcomes other than degree attainment.

First, all of these analyses could be expanded upon with the inclusion of financial aid information. Texas offers a numbers of need-based and merit-based aid programs in addition to the federal programs available to its residents. Future studies would benefit from making use of this information, particularly in examining degree outcomes for vulnerable students.

Secondly, I have set this study in Texas—a state with a vast community college system and an excellent student-level administrative dataset. Future analyses would benefit from conducting similar studies in other state with similar data offerings. The multiple quasi-experimental techniques used to address selection problems present in the analyses could also be refined depending on data available and context.

Third, I have examined these outcomes at the state level, while including institutional-level covariates. Future analyses may benefit from examining these patterns on a more micro level using mixed methods. Of particular interest in this vein of research would be examining the differential outcomes by race and unearthing factors beyond those observable characteristics in the state database. An exploration that warrants further investigation is examining what is that causes Black students who begin at a four-year institution to graduate at such higher rates than Black students who begin at a community college.

Fourth, future studies would benefit from examining outcome aside from degree attainment. A key benefit in the Texas dataset and others like it is the inclusion of wage data. Perhaps future studies could examine labor market returns for community college graduate and build upon a growing body of literature that explores wages as a result of varying types of educational opportunities.

The Role of the Community College in Texas

As a final note, I have focused on the role of the community college in facilitating transfer and degree attainment for those students graduating from high school and immediately enrolling in a community college. With swelling enrollments and rising tuition in the four-year sector, the role of the community college in Texas appears to be an expanding one: a role that will come to include educating many more first-time enrollees and may benefit from policies aimed at increasing credit hours while decreasing working hours of students. While this is certainly an important and critical role, this is not, however, the only role of the community college in Texas. Indeed, nearly two-thirds of those enrolled in the community college are students entering or returning to higher education later in life. Community colleges also provide lifelong learning opportunities and locations for community enrichment. While I have examined the role of the community college in Texas as an agent for access to higher education and continued student success, I have merely touched lightly on the multi-faceted and diverse role of the community college in Texas—a role that warrants further exploration in a holistic and diverse nature.

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